Abstract

COMMUNITY FLOOD HAZARD MITIGATION AND THE COMMUNITY RATING SYSTEM OF NATIONAL FLOOD INSURANCE PROGRAM

by

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April 2012

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Major Department: Coastal Resources Management Ph.D. Program

Flooding events, including coastal, estuarine, and riverine floods, cause considerable losses to individuals and businesses in the United States. In recent decades, over 80 percent of disaster losses nationwide have been attributed to flooding. Many flood hazard mitigation measures, including programs designed to inform people about potential hazards, plans that promote disaster preparedness, and regulations designed to limit vulnerability though building standards, have elements of local public goods in that they provide benefits for an entire community and agents in the community are not excluded once the goods have been made available. As such, local governments play a critical role in flood hazard mitigation. Policy makers need information to allow them to better understand community hazard mitigation behavior and evaluate the effectiveness of local flood mitigation projects so they can develop impactful management strategies. The analyses in this dissertation provide such information.

This dissertation focuses on the Community Rating System (CRS) of the National Flood Insurance Program (NFIP), which credits local floodplain management activities and provides flood insurance premium discounts for households and businesses in a community. In order to motivate flood insurance purchase and promote increased flood hazard mitigation, the CRS credits 18 community floodplain management activities in four broad categories: (1) public information; (2) flood mapping and regulation; (3) flood damage reduction; and (4) flood preparedness. FEMA classifies the portfolio of community flood management practices on a ten point scale, reflecting the overall level of mitigation. The CRS classification determines premium discounts for insurance purchases under the NFIP. Discounts range from five to 45 percent. Programs like CRS seek to incent cooperation amongst federal, state, and local governments rather than impose top-down mandates that require particular mitigation approaches. By offering individual financial inducements for community-level flood hazard mitigation, CRS is an incentive-based, bottom-up cooperative approach to risk management that could address some of the shortcomings of other cooperative approaches to environmental management. Through an improved understanding of CRS, state governments and FEMA can better encourage participation in the CRS and similar programs in order to provide for better protection from natural hazards. It also allows for a better targeting of resources to improve hazard vulnerability

This dissertation has three major chapters. Chapter 3, which is entitled “Participation in the Community Rating System of NFIP: An Empirical Analysis of North Carolina Counties”, tests a number of hypotheses offered by previous researchers regarding factors that motivate local hazard management initiatives through an examination of patterns in CRS participation across all 100 North Carolina counties from 1991 to 2002. Specifically, we examine the influence of flood experience, hydrological risk, local capacity, and socioeconomic factors on county hazard mitigation decisions. Results indicate that flood history and physical risk factors increase likelihood of local hazard mitigation adoption. We find evidence that the probability of CRS participation is lower in counties with a greater proportion of senior citizens and greater level of education, and that flood hazard mitigation activities at the county level are more likely when a greater number of nested of municipalities participate in CRS.

Chapter 4, which is entitled “Evaluation of the Community Rating System of National Flood Insurance Program – An Application of Propensity Score Matching”, develops innovative ways to assess the performance of the CRS. The true performance of CRS can be determined if one compares a meaningful outcome – like the average property damage during flooding events – for each CRS participant with their untreated selves during the same event. However, it is impossible to observe what would have happened to CRS participants in absence of their participating in the CRS (lack of counterfactual). The primary objective of chapter 4 is to use propensity score matching (PSM) methods to correct sample selection bias due to observable differences between the CRS participants and comparison groups. Although there is substantial variation in the results, the findings show that all of the effects are in the same direction, indicating CRS effectively reduces the average property damage due to flood hazard.

Chapter 5, which is entitled “Estimation of a Dynamic Model: Policy Learning in Hazard Mitigation”, addresses the dynamic nature in flood hazard mitigation policy learning by examining the patterns in Community Rating System (CRS) scores across all 100 counties in North Carolina from 1995 to 2010, with controls of flood experience, hydrological risk factors, local capacity, and socioeconomic factors. It is important for local governments to maintain stability and transparency in planning and policy-making processes, so that agents and institutions can form reasonable expectations upon which to make development and investment decisions. As a result, the establishment of a new framework of hazard mitigation presents a considerable challenge, involving a change of momentum which requires commissioner meetings, public hearings, and ordinance revisions, all of which are costly. Therefore, we postulate that hazard mitigation policy evolution in response natural disasters can be described in terms of a dynamic mechanism. The dynamic panel model is characterized by the presence of a lagged dependent variable among the regressors, incorporating both dynamics and individual-specific effects. The result show that once local governments regulate their floodplains in ways that go beyond the minimum required by the NFIP, they tend to improve flood hazard mitigation incrementally despite changes in staff and shifts in local political regimes.

COMMUNITY FLOOD HAZARD MITIGATION AND THE COMMUNITY RATING SYSTEM OF NATIONAL FLOOD INSURANCE PROGRAM

A Dissertation

Presented to the Faculty of the Coastal Resources Management Ph.D. Program

East Carolina University

In Partial Fulfillment of the Requirements for the Degree

Doctor of Philosophy in Coastal Resources Management

by

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April 2012

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To My Parents

AKNOWLEDGEMENTS

I would like to give my sincere thanks to my Ph.D. degree advisor, Craig Landry, for mentoring me and encouraging me to explore a range of different research topics. Thank you for teaching me how to think like a professional researcher and how to approach problems with both rigor and creativity. My grateful thanks are also due, in particular, to Jamie Kruse for her supporting me during these past five years. I feel as though my experiences in the Center for Natural Hazard Research at East Carolina University have exceeded the opportunities normally bestowed on graduate students. My special thanks also go to John Bishop. Much of the advice and encouragement you have given me will have a long lasting impact on my life. I would also like to thank the rest of my committee members, Robert Christian, Thomas Crawford, Daniel Marcucci, and Richard Spruill for their contributions to my dissertation. Finally, I thank all the faculty members in the Coastal Resources Management Program and the Department of Economics at East Carolina University for their helpful career advice and suggestions in general.

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Chapter 1: Introduction

While the dynamics of weather patterns play an important role in the recent growth of damaging floods in the U.S., intensive development in floodplains and extensive population growth in low lying and coastal areas have increased human beings' exposure to flood hazard. The communities that engage in hazard mitigation planning and management activities are less prone to flood hazard and recover faster from disaster than those communities which do not. Many mitigation measures, including programs designed to inform people about potential hazards, plans that promote disaster preparedness, and regulations designed to limit vulnerability though building standards, have elements of local public goods in that they provide benefits for an entire community and agents in the community are not excluded once the goods have been made available. As such, local governments play a critical role in flood hazard mitigation.

This dissertation focuses on one particular flood hazard mitigation program, the Community Rating System (CRS) of the National Flood Insurance Program (NFIP), which credits local floodplain management activities and provides flood insurance premium discounts for households and businesses in a participating community. In order to motivate flood insurance purchase and promote increased flood hazard mitigation, the CRS credits 18 community floodplain management activities in four broad categories: (1) public information; (2) flood mapping and regulation; (3) flood damage reduction; and (4) flood preparedness. FEMA classifies the portfolio of community flood management practices on a ten point scale, reflecting the overall level of mitigation. The CRS classification determines premium discounts for insurance purchases under the NFIP. Discounts range from five to 45 percent. Programs like CRS seek to incent cooperation amongst federal, state, and local governments rather than impose top-down mandates that require particular mitigation approaches. By offering individual financial inducements for community-level flood hazard mitigation, CRS is an incentive-based, bottom-up cooperative approach to risk management that could address some of the shortcomings of other cooperative approaches to environmental management. Through an improved understanding of CRS, state governments and FEMA can better encourage participation in the CRS and similar programs in order to provide for better protection from natural hazards. It also allows for a better targeting of resources to improve hazard vulnerability.

Since CRS uses standardized quantitative measures for representing local hazard mitigation activities, it provides an excellent source of information for empirical analysis of community hazard mitigation decisions. As such, the focus of this dissertation is on quantitative analysis of participation, CRS point totals, and flood-related property damages, employing variants of regression analysis. Regression models provide a useful framework for analyzing large, multi-faceted datasets with many covariates. Often times, under fairly weak assumptions, this framework is capable of simultaneously testing many different hypotheses regarding the influence of exogenous factors on one or more dependent variables. Regression models provide information on conditional correlations that include direction, magnitude, and statistical significance (while controlling for other factors) – in many instances, or with additional assumptions, these correlations are indicative of causal relationships. Thus, regression is a valuable analytical approach for conducting statistics with large and complex datasets that conform to the requirements of the approach (with binary, categorical, or various scaled measures).

We acknowledge some limitations of quantitative analysis. The approach is somewhat limited to analyzing factors that can be quantified (though some specifications of regression models allow for unobserved factors). Regression analysis is not well suited for exploring contextual factors or discovering latent patterns or idiosyncrasies in underlying processes. For these and other reasons, qualitative research procedures, such as interviews, focus groups, case studies, and textual analysis, are also useful approaches for study social phenomena. These approaches are generally complementary to quantitative analysis, and so-called "mixed methods" approaches can be instrumental in creating new knowledge. Nonetheless, the focus of this dissertation is on quantitative methods. But, we note that mixed methods remain a viable and important approach for future research.

The plan of the dissertation is as follows. The work format will be organized into two primary sections. The first section includes this introduction and provides an overview of the entire dissertation. Traditional flood damage mitigation focused on structural engineering solutions, such as dams, levees, and channel improvements. Non-structural measures include zoning ordinances, building codes, flood warning systems, emergency planning, flood insurance, and so forth. Because this dissertation focuses primarily on non-structural hazard mitigation, the second chapter provides details on non-structural flood mitigation, as recognized by the Community Rating System of the National Flood Insurance Program. These sections are meant to help provide an interdisciplinary audience with the necessary background for reading the empirical studies.

The second section, which is divided into three chapters, comprises the dissertation's empirical focus. The first portion, which is entitled "Participation in the Community Rating System of NFIP: An Empirical Analysis of North Carolina Counties", tests a number of hypotheses offered by previous researchers regarding factors that motivate local hazard management initiatives through an examination of patterns in CRS participation across all 100 North Carolina counties from 1991 to 2002. Specifically, we examine the influence of flood experience, hydrological risk, local capacity, and socioeconomic factors on county hazard mitigation decisions. Results indicate that flood history and physical risk factors increase likelihood of local hazard mitigation adoption. We find evidence that the probability of CRS participation is lower in counties with a greater proportion of senior citizens and greater level of education, and that flood hazard mitigation activities at the county level are more likely when a greater number of nested of municipalities participate in CRS.

The second portion, which is entitled "Evaluation of the Community Rating System of National Flood Insurance Program – An Application of Propensity Score Matching", develops innovative ways to assess the performance of the CRS. The true performance of CRS can be determined if one compares a meaningful outcome – such as the average property damage during a flood event – for a participating county with their untreated selves. However, it is impossible to observe what would have happened to CRS participants in absence of their participating in the CRS – there is no counterfactual. The primary objective of this chapter is to use propensity score matching (PSM) methods to correct sample selection bias due to observable differences between the CRS participants and comparison groups. Although there is substantial variation in the results, the findings show that all of the effects are in the same direction, indicating that CRS effectively reduces the average property damage due to flood hazard. The methodology in this chapter makes important advances in understanding how to measure and conceptualize the performance of a mitigation program as it is applied to reducing the adverse effects of flooding. The study also yields insights into performance evaluation of mitigation plans for other natural disasters, such as hurricanes, fire, and earthquakes.

The third portion, which is titled which is entitled "Estimation of a Dynamic Model: Policy Learning in Hazard Mitigation", addresses the dynamic nature of flood hazard mitigation policy learning by examining the patterns in CRS scores across all 100 North Carolina counties from 1995 to 2010, with controls of flood experience, hydrological risk factors, local capacity, and socioeconomic factors. It is important for local governments to maintain stability and transparency in planning and policy-making processes, so that agents and institutions can form reasonable expectations upon which to make development and investment decisions. As a result, the establishment of a new framework of hazard mitigation can present a considerable challenge, involving a change of momentum which requires commissioner meetings, public hearings, and ordinance revisions, all of which are costly. Therefore, we postulate that hazard mitigation policy evolution in response to natural disasters can be described in terms of a dynamic mechanism. The dynamic panel model is characterized by the presence of a lagged dependent variable among the regressors, incorporating both dynamics and individual-specific effects. The result show that once local governments regulate their floodplains beyond the minimum levels required by the NFIP, they tend to make incremental improvements in mitigation over time despite changes in staff and shifts in the local political regime. Each empirical study will include a discussion on the policy implications of any relevant findings. Following these chapters, the dissertation will conclude with a discussion of research extensions and directions for future development.

Chapter 2: Flood Hazard Mitigation and the Community Rating System of National Flood Insurance Program

Flooding events, including coastal, estuarine, riverine, and flash floods, cause considerable losses to individuals and businesses in the United States. In recent decades, over 80 percent of all presidentially declared disaster losses have been attributed to flooding. The average damages from floods in the United States are $115 million per week (Burby 2001), and property damages caused by flooding have been increasing at an alarming rate. Data from Federal Emergency Management Agency (FEMA) indicate that significant floods caused more than $5 billion in average annual damage to property from 1993 to 2007 compared to about $0.6 billion from 1978 to 1992.

Scholars generally recognize two types of hazard mitigation that can be adopted for flood risk management. Traditionally, flood damage mitigation focused on structural engineering methods, such as dams, levees, and channel improvements. FEMA (1986) estimates over $7 billion in public monies were spent on large scale flood control works between the mid-50s and mid-80s. Zahran, et al. (2008) estimate that an increase in the number of dams in Texas decreased the odds of death or injury due to flood by 22.6 percent. Due to increasing population and development pressures, however, average annual flood property damage in the U.S. is rising continually. The overwhelming expense and adverse environmental effects of structural flood mitigation works have lead to more emphasis being place on smaller scale non-structural mitigation methods. Non-structural measures include land use planning, zoning ordinances, building codes, flood warning systems, emergency planning, flood insurance, and so forth. This study focuses primary attention on non-structural mitigation.

In the federal-state-local floodplain management nexus, each level of government can play a role in flood loss reduction. The federal government has preeminent regulatory authority and financial capacity to provide assistance in flood management and protection projects and administer disaster relief to flood victims. Given increasing pressure on federal funds, the high cost of structural flood protection works, and community requests for more regulatory control, there has been a movement towards building stronger state capacity to implement flood loss programs (Burby 2006, ASFPM 2007). Experience suggests that effective local management occurs in the presence of strong state floodplain management programs. Burby (2005) finds evidence that insured losses to residential property from natural disaster are significantly reduced if the state mandates local comprehensive plans with hazard mitigation elements (which are currently optional in some U.S. states). Other roles of state governments include providing direct technical assistance to local government, training local floodplain mangers, managing or assisting with hazard mitigation activities, and implementing permit processes. Under the authority delegated by federal and state governments, local governments are primarily responsible for zoning and planning, while sharing in the management of hazard mitigation activities within their jurisdictions. As such, local governments can play a critical role in flood hazard mitigation (Prater and Lindell 2000). Many hazard mitigation measures have elements of local public goods, as they provide community-wide benefits and individuals in the community are not excluded once they have been made available.

2.1 National Flood Insurance Program (NFIP)

As a part of floodplain management and flood loss reduction programs, the National Flood Insurance Program (NFIP) was designed as a non-structural approach to flood risk management, and the program was seen as a complement to structural flood protection works

(Kunreuther and Roth 1998). In order to provide recovery resources for flood disaster (Kunreuther and Roth 1998), reduce the public burden of disaster relief payments (Kriesel and Landry 2004), and dissuade uneconomic uses from locating in flood hazard areas (Burby 2001), the US Congress passed the National Flood Insurance Act of 1968. This act created the National Flood Insurance Program (NFIP), which has two primary goals: identification of flood hazard at a fine spatial scale and mitigation of hazard through planning, zoning, improved building standards, and provision of insurance for businesses and households (Burby 2001). NFIP is a voluntary joint venture between federal and state governments, private insurance companies, and local communities. Participating communities are required to adopt and enforce floodplain management ordinances and construction standards in flood hazard areas (Dixon, et al. 2006). The federal government is primarily responsible for conducting detailed hydrological assessments used to produce flood insurance rate maps (FIRMs) and setting flood insurance premium schedules. The state governments hold regulatory authority over insurance contracts in their state. Under the Write Your Own (WYO) program, private insurers sell and service policies, with the premiums (net of administrative fees that go to private insurers) deposited in a federally operated flood insurance fund, which then pays all claims (Kunreuther 1996). Based on FEMA's statistics, currently more than 20,000 communities across the United States and its territories participate in the NFIP (roughly 75 percent of all communities in the United States) with an estimated 4.5 million policies in force by 2006 (Dixon, et al. 2006).

FEMA estimates that flood damage is reduced by nearly $1 billion a year as a result of the NFIP floodplain management regulations for new construction. Prior studies, however, highlight numerous shortcomings of the program. First, community participation does not necessarily imply that individual property owners will opt to purchase flood insurance.

According to FEMA, only 2.5 million of the nearly 10 million households in flood-prone areas had purchased flood insurance by 1995 (Kunreuther 1996). Dixon, et al. (2006) estimate the NFIP nationwide market penetration rate for signal family homes in Special Flood Hazard Areas (SFHAs) at 49 percent in 2003. Second, Flood Insurance Rate Maps (FIRMs), which FEMA uses to delineate flood hazard areas within a community, are not updated frequently. Thus, the risk designation conveyed by FIRMs can produce severe underestimates in some areas (Michel-Kerjan and Kousky 2010). Third, FEMA offers Pre-FIRM properties explicitly subsidized premiums, which are 30 to 40 percent of the full-risk premium. Price Waterhouse Coopers (1999) concludes that the premiums of some Pre-FIRM properties are much less than what would be required to cover payouts, partly due to repetitive losses for particular parcels. Moreover, there exists significant skepticism over whether NFIP rate schedules for new construction (referred to as “actuarial”) accurately reflect expected loss; prior to the 2005 hurricane season (a record loss year), NFIP exhibited a cumulative deficit of $3 billion after 37 years of operation (Wharton 2008). Finally, research in coastal housing markets has produced evidence that flood zone designation and insurance premiums convey risk information to potential buyers in housing market; thus allowing premiums to reflect objective risk assessment is important in providing incentives for better individual investment and mitigation decision (Krutilla 1966; MaDonald, et al. 1990; Bin, Kruse, and Landry 2008; Bin, et al.2008). Chivers and Flores (2002), however, provide contradictory evidence suggesting a majority of people in Colorado did not acquire information about flood risk and cost of insurance until after property purchase.

2.2 Community Rating System (CRS)

In order to increase flood hazard awareness, motivate flood insurance purchase, and promote flood hazard mitigation, the CRS was instituted by the Federal Insurance Administration (FIA) as a voluntary program for NFIP-participating communities. The goals of this program are to reduce flood loss through community-level mitigation projects, facilitate accurate insurance rating, and promote the public's awareness of flood hazard and insurance. When flood management activities of a CRS community comply with these goals, flood insurance premiums for its citizenry are adjusted to reflect mitigation efforts to effectively reduce flood risk (Kunreuther and Roth 1998).

The CRS credits 18 community floodplain management activities which are organized under four broad categories: (1) Public information, (2) Flood mapping and regulation, (3) Flood damage reduction, and (4) Flood preparedness (see Table 2.1). FEMA classifies the portfolio of community flood management practices on a ten point scale, reflecting the overall level of mitigation. The CRS classification determines the premium discounts which range from 0 percent to a maximum of 45 percent (see Table 2.2). All communities that are in full compliance with the NFIP and are in the regular phase of the program but have not taken additional measures to reduce flood risks receive a CRS rating of 10 – no flood insurance premium discount. CRS class 1 requires the most credit points and gives the greatest premium discount of 45%. Each year, local governments can submit documentation to a specialist from the Insurance Services Office, Incorporated (ISO – an independent contractor that handles certification for CRS) to verify that they are continuing to perform hazard management activities for which they receive CRS credit, and they can apply to receive credit for new hazard management initiatives that improve their classification.

CRS provides premium discounts for residents in a qualified community in an effort to encourage hazard mitigation and individual participation in NFIP. Since rates are adjusted to reflect risk, CRS can help to alleviate moral hazard. By offering CRS credit for updating of flood risk data, information on flood hazard can be updated, expanded, and refined, and may become more accurate over time, leading to better delineation of flood hazard areas within a community. Flood Damage Reduction activities (series 500 - see Table 2.1) include acquisition, relocation, or retrofitting of existing high-risk structures, which could prevent repetitive losses. Finally, CRS credit is provided if a community's real estate agents (and others involved in land development and investment decisions) advise prospective floodplain occupants about flood hazard and the flood insurance purchase requirement for mortgaged properties in the SFHA. In an analysis of 832 large scale flooding events in Texas between 1997 and 2001, Zahran, et al. (2008) find suggestive evidence that community hazard mitigation programs promoted by CRS resulted in significantly lower loss of human lives. Since CRS uses standardized quantitative measures for representing local hazard mitigation activities, it provides an excellent source of information for empirical analysis of community hazard mitigation decisions.

Table 2.1: Community Rating System (CRS) Activities and Credit Scores

<table>
<tr><th>Series</th><th>Descriptions</th><th>Creditable Activities</th><th>Points</th></tr>
<tr><td rowspan="6">Public Information (300)</td><td rowspan="6">CRS will credit those local activities that advise people about the flood hazard, flood insurance and flood protection measures.</td><td>1. Elevation Certificates</td><td>162</td></tr>
<tr><td>2. Map Information</td><td>140</td></tr>
<tr><td>3. Outreach Projects</td><td>380</td></tr>
<tr><td>4. Hazard Disclosure</td><td>81</td></tr>
<tr><td>5. Flood Protection Information</td><td>102</td></tr>
<tr><td>6. Flood Protection Assistance</td><td>71</td></tr>
<tr><td rowspan="5">Mapping and Regulations (400)</td><td rowspan="5">CRS provides credit to communities that enact and enforce regulations that exceed the NFIP's minimum standards so that more flood protection is provided for new development.</td><td>1. Additional Flood Data</td><td>1346</td></tr>
<tr><td>2. Open Space Preservation</td><td>900</td></tr>
<tr><td>3. Higher Regulatory Standards</td><td>2740</td></tr>
<tr><td>4. Flood Data Maintenance</td><td>239</td></tr>
<tr><td>5. Stormwater Management</td><td>670</td></tr>
<tr><td rowspan="4">Flood Damage Reduction (500)</td><td rowspan="4">This series of activities addresses flood damage to existing buildings. It complements the previous series that dealt with preventing damage to new development.</td><td>1. Floodplain Management Planning</td><td>359</td></tr>
<tr><td>2. Acquisition and Relocation</td><td>3200</td></tr>
<tr><td>3. Flood Protection</td><td>2800</td></tr>
<tr><td>4. Drainage System Maintenance</td><td>330</td></tr>
<tr><td rowspan="3">Flood Preparedness (600)</td><td rowspan="3">Activities in this series include actions that should be taken to minimize the effects of a flood on people, property, and building contents.</td><td>1. Flood Warning Program</td><td>225</td></tr>
<tr><td>2. Levee Safety</td><td>900</td></tr>
<tr><td>3. Dam Safety</td><td>175</td></tr>
</table>

Source: NFIP CRS Coordinator's Manual (2007).

Table 2.2: CRS Credit Points Earned, Classification Awarded, and Premium Reductions

Score	Credits	Discount in SFHA*	Discount in non-SFHA**
1	4,500+	45%	10%
2	4,000-4,499	40%	10%
3	3,500 – 3,999	35%	10%
4	3,000 – 3,499	30%	10%
5	2,500 – 2,999	25%	10%
6	2,000 – 2,499	20%	10%
7	1,500 – 1,999	15%	5%
8	1,000 – 1,499	10%	5%
9	500 – 999	5%	5%
10	0 – 499	---	---

*Special Flood Hazard Area
**Preferred Risk Policies are available only in B, C, and X Zones for properties that are shown to have a minimal risk of flood damage. The Preferred Risk Policy does not receive premium rate credits under the CRS because it already has a lower premium than other policies. The CRS credit for AR and A99 zones are based on non-SFHAs (B, C, and X). Credits are: scores 1-6, 10% and scores 7-9, 5%. Premium reductions are subject to change.

Source: NFIP CRS Coordinator's Manual 2007.

Chapter 3: Participation in the Community Rating System of NFIP: An Empirical Analysis of North Carolina Counties

In this chapter, we synthesize previous research and formulate and test a number of hypotheses regarding participation in CRS. We examine the influence of flood experience, hydrological risk factors, local capacity, and socioeconomic factors on community hazard mitigation decisions as indicated by CRS participation, through examination of patterns in CRS involvement across all 100 North Carolina counties from 1991 to 2002. We use panel data models in order to control for unobserved cross-sectional level heterogeneity within a multiple regression framework. Our goal is an improved comprehension of why some local governments adopt hazard mitigation measures while others do not. The results contribute to a better understanding of collective decision making for environmental management (specifically natural hazard risk) and help to assess vulnerability by providing information on mitigation decisions. Through an improved understanding of the factors that influence the initiation and implementation of mitigation policies, FEMA and state governments can better encourage participation in the CRS and similar voluntary, incentive-based programs in order to provide for improved environmental management.

The following section presents detail on previous literature on natural hazard mitigation and formulates research hypotheses. Section 3 describes the data used for analysis. Section 4 presents the random effects Probit model which we employ to study CRS participation. Section 5 interprets the regression results.

3.1 Literature Review: Hazard Mitigation

The Federal government's role in flood risk management originated with the Flood Control Act of 1928, which authorized the U.S. Army Corps of Engineers to design and construct projects for the control of floodwaters. Passage of the National Flood Insurance Act in

1968, marked a movement towards land-use planning, construction standards, and federally backed flood insurance (Pasterick 1998). Political pressures, however, have created impetus for increasing amounts of disaster relief payments for flood victims, despite the fact that many communities have allowed risky development in floodplains (ASFPM 2007; Michel-Kerjan and Volkman-Wise 2011). The expectation of disaster assistance can create a disincentive for self-protection, insurance, and mitigation, because the federal government significantly aids the reconstruction after each natural disaster (Beatley 1989; Coate 1995; Burby, et al. 1999; Haddow and Bullock 2003). In order to address local capacity and encourage local commitment (rather than facilitating further development in floodplains), the National Academy of Public Administration (NAPA) has recommended establishing a "cooperative intergovernmental system" to build state and local capacity in place of *ex post* disaster assistance (Godschalk, et al. 1998). The emerging cooperative system has focused natural hazard mitigation efforts at the state and local level, with the federal government providing support in the forms of resources and guidance. Within this framework, local hazard mitigation efforts can be enhanced by direct regulation, incentive programs, and supervision of flood loss reduction programs (ASFPM 2007).

In accord with the recommendations of NAPA and the delegation of responsibility for planning activities, there appears to be a general consensus in the planning literature that hazard mitigation policy should be carried out at the local level. As such, local governments play a critical role in flood hazard mitigation (Mileti 1999; Prater and Lindell 2000). Floodplain management, however, is sometimes viewed by local government personnel as someone else's responsibility (Burby, et al. 1985), and the reluctance of local elected officials to advocate mitigation measures is identified as a primary impediment to hazard mitigation (Burby 1998;

Burby and May 1998). Just as individuals are wont to, local government officials often underestimate the risks involved in developing flood plain areas unless they have recently experienced a flood event. The occurrence of floods can influence political will and public support of hazard mitigation (Clary 1985; Burby and Dalton 1994). Disaster events can open "windows of opportunity" by exposing vulnerability and focusing the political agenda on hazard mitigation issues (Kingdon 1984; Berkes 2007). Protracted planning, permitting, and implementation procedures, however, may introduce significant time lags between the occurrence of hazard events and successful completion of mitigation projects (NOAA 2010). Burby and French (1985) conclude that while a window of opportunity may exist in the aftermath of disaster, prospects for improved hazard mitigation dim rapidly as political attention and local efforts turn to recovery and a return to normalcy. Moreover, in his events-related policy study, Birkland (1998) concludes few will take advantage of a disaster event to pursue the policy change without some sort of policy community or advocacy coalition providing support and coordination.

Since natural hazards are large scale events, mitigation and planning require substantial resources. Thus, local government potential for hazard mitigation is largely dependent upon local capacity – in particular, trained staff and budget (Kunreuther and Roth 1998). While knowledge of local circumstances increase as one moves from state or national level down to local jurisdictions, local capacity is comparatively much more limited and varies widely across locales (Perry and Lindell 2003). The amount of governmental resources that are allocated to hazard mitigation is dependent on the available fiscal resources in a jurisdiction (Prater and Lindell 2000). Moreover, the extent of on-hand resources and the array of human capital may differ significantly from one community to another, due to idiosyncratic differences in experience, local culture, and histories. Previous researchers have examined policy implementation and pointed out that strong mitigation capacity is most likely to be found in larger communities and communities with higher property values (Burby and French 1981; Godschalk 2003). Therefore, local government revenue, which is mainly derived from taxes on property, is likely to directly influence community mitigation capacity. The benefits of hazard mitigation, however, are only realized after disasters occur and are difficult to quantify, while the costs are incurred immediately and are easy to calculate. Therefore, other problems, such as crime control and improving the quality of education, may garner more attention and funding compared with hazard mitigation projects (Prater and Lindell 2000).

An analysis of the effectiveness in floodplain management programs in 1,203 NFIP jurisdictions shows that varying constraints such as flood risk factors, land use in flood hazard areas, and demographic characteristics, require different mixes of program components in order to mitigate hazards (Burby and French 1985). Posey (2009) examines the influence of local socioeconomic status on the adaptive capacity of municipal governments, using CRS participation and classes as proxies for local capacity to adapt to environmental hazards. His study employs cross-sectional regression analysis to explore the effects of population, historical flood losses, and socioeconomic factors (including income, education, race, housing values, etc.) on mitigation levels and premium discounts in CRS for over 10,000 communities across the US. In addition, Posey examines the influence of local government structure (presence of city manager), municipal budget, and cities' net valuation on CRS participation and premium discounts for New Jersey communities (also using cross-sectional regression models). He finds a positive effect of historical flood losses on flood hazard mitigation and a negative effect attributed to population. Using variables derived from principle component analysis, he finds evidence that hazard mitigation is more likely to occur in affluent communities with greater levels of education and lower proportions of minority households. The results make intuitive sense, as citizens can apply direct and indirect pressure to motivate hazard mitigation on the part of local government officials through elections, town hall meetings, editorials in local papers, and public opinion polls, which provide an opportunity for feedback on the performance of local officials (Prater and Lindell 2000). While the causal mechanism between individual socio-economic status and local government's adaptive capacity remains to be empirically verified, the results highlight correlation patterns among flood hazard mitigation efforts and community characteristics.

Brody, et al. (2009) examine adaptive management and policy learning for flood mitigation as reflected in CRS scores in Florida counties from 1999 to 2005. Specifically, they track annual point totals for the four CRS mitigation series (described in Table 2.1) for 52 of the 67 Florida counties that exhibit some level of voluntary participation in the CRS. They use population-adjusted measures of CRS points and regression covariates to account for both participating counties and nested municipalities, and examine the influence of hydrologic conditions, flood disaster history, socioeconomic, and human capital controls on CRS points. Their results suggest that flood history induces flood policy adaptation and the frequency of events is more influential than the level of damage; jurisdictions with greater proportion of land in the 100-year floodplain have lower CRS points, which the authors attribute to higher levels of mitigation expense. CRS points tend to be greater in wealthier and more highly educated jurisdictions. Local governments in Florida have tended to focus on less expensive mitigation measures, such as information provision and flood information updating, to earn CRS points, rather than costly structural measures, such as parcel acquisition and retro-fitting. The body of research on flood hazard mitigation provides important insight into and evidence of aspects that influence local jurisdictions' willingness and ability to address flood risk management. Critical questions remain, however, as to the significance, strength, and relative importance of driving factors in implementation of hazard mitigation policies at the local level – what distinguishes those communities that are active in flood hazard mitigation from those that are not.

In summary, the literature on flood hazard mitigation suggests that local risk factors, risk information, historical flooding experience, political agency, public participation in planning, and financial capacity can be important in determining local flood hazard mitigation efforts. By exposing vulnerability and focusing the political agenda, hazard events can open a "window of opportunity" for initiation of flood hazard mitigation. But, this window may be short-lived, as other matters – such as crime and education – press for attention of citizens and local bureaucrats. The literature suggests that characteristics of the population, such as income, housing values, education, and ethnicity can influence hazard mitigation, presumably through direct and indirect citizen involvement in local politics (but perhaps other ways as well).

3.2 Objectives

We examine participation in CRS for all 100 North Carolina counties from 1991 – 2002. This time period covers the inception of CRS to the year in which the last NC County enrolled. Since CRS credit is only awarded upon verification by an external party (ISO), active participation in CRS includes adoption and implementation of (at least some) hazard mitigation efforts. As such, we hope to learn about the importance and relative magnitude of factors that influence communities' willingness to adopt and implement incentive-based hazard mitigation measures.

We test a number of hypotheses offered by previous researchers to uncover the factors that motivate local hazard management initiatives through an examination of patterns in participation in CRS across a panel dataset of NC Counties. We posit the following hypotheses:

- **H1**: *Historical Flood Experience*: Counties with greater historical flood experience (such as flood events and property damage) are more likely to participate in CRS.
- **H2**: *Window of Opportunity*: Counties with recent flood experience (such as flood events and property damage) are more likely to participate in CRS.
- **H3**: *Flood Risk Factors*: Counties with higher overall level of hydrological risk (average annual precipitation, proportion of water bodies to surface area, and coastal location) are more likely to participate in CRS.
- **H4**: *Local Capacity*: Counties with greater financial resources (such as property tax revenue) are more likely to participate in CRS.
- **H5**: *Crowding Out*: Counties with more severe day-by-day social problems in the recent past (such as high crime and poor school quality) are less likely to participate in CRS.
- **H6**: *Socioeconomic Characteristics*: Counties' likelihood of participation of CRS is influenced by socioeconomic characteristics (such as population, age distribution, education level, and number of housing units).

We elaborate on these hypotheses and the data used to test them in the next section.

3.3 Data

The list of CRS communities and their 2008 CRS scores are available on the FEMA website (http://www.fema.gov/pdf/nfip/manual200805/19crs.pdf). With publicly available data, we are unable to observe many of the variables of interest at scales below the county level, so we confine our analysis to NC counties and save a multi-jurisdictional analysis for future research. We focus on the time period 1991 to 2002; CRS was initiated in 1990 and our chosen time period encompasses initial enrollment activities of all participating North Carolina counties. A drawback associated with focusing on this period of time is that some data (such as digital flood maps) are unavailable. Figure 3.1 displays a map depicting all NC counties that have participated in CRS.

NC Counties that did not participate in NFIP during 1991-2002 are coded as non-participants in CRS (*CRS_dummy* = 0). As of 1991, however, most NC Counties were enrolled in NFIP, so that they could apply for and receive credit for flood hazard mitigation activities recognized by CRS. If these counties undertake no additional flood hazard mitigation activities or fail to apply for CRS credit, they receive a CRS score of 10 – no flood insurance discount; these counties are coded as non-participants (*CRS_dummy*=0). Any counties that received less than 500 CRS points in any given year are also counted as non-participants (*CRS_dummy*=0). We cannot observe local flood hazard mitigation activities that result in less than 500 points, as they are not included in the CRS-points data series. Nonetheless, the *CRS Coordinator's Manual* contains an easy-to-use checklist that allows local officials to determine if their community currently undertakes enough activities to attain Class 9 (>499 CRS points). Many recommended activities can be implemented for a relatively low up-front cost (e.g. public information activities Series 300-responding to inquires to identify a property's FIRM zone can earned up to 138 CRS points) (FEMA 2007, page 120-3). Any mix of flood hazard mitigation activities from table 2.1 that results in 500 points is sufficient to attain a score of 9, and additional activities can lower the score. Thus, counties with a score of 9 or less are coded as CRS participants (*CRS_dummy*=1).

Since we do not observe flood hazard mitigation activities that result in less than 500 points, our estimates can be viewed as conservative (requiring a threshold level of activity before mitigation is recognized in the statistical model). Moreover, since we use the CRS framework to identify mitigation activities, our model accounts for adoption and implementation (as is generally required for CRS credit), and we do not analyze mitigation activities that might occur outside of the CRS framework. On average, 17% of NC Counties participated in CRS during 1991 – 2002, with a high of 20% (in 1996) and a low of 8% in the initial year (1991). Figure 3.2 shows the proportion of participating counties over time. At the end of the time-series, 18 of the 100 NC counties were participating in CRS.

Table 3.1 presents a summary of the variables to be used in our analysis. The explanatory variables are organized under four broad categories. First, six flood experience variables that were collected from National Climate Data Center (NCDC) are proposed to account for the history and severity of community flood hazard. These variables include data on flood events and property damage in each county. We use ten years flood experience (1980-1989) prior to CRS, fixed for a given county in our longitudinal dataset, to test **H1**. We postulate that greater historical experience with floods (in terms of events and property damage) will motivate more stringent hazard mitigation, increasing the likelihood of CRS participation. While hazard exposure can influence political will and build public support of hazard mitigation (Kingdon 1984; Clary 1985; Burby and Dalton 1994; Berkes 2007), laborious and protracted planning, permitting, and implementation processes may introduce significant time lags between hazard events and successful completion of mitigation projects (NOAA 2010). Nonetheless, the occurrence of floods can focus the political agenda on the importance of flood hazard mitigation, especially if flood damages are severe. To account for this, we use previous one year and two years flood events and flood-related property damage to test **H2**. Our community flood experience variables thus include events in the distant and recent past in order to account for a legacy of flooding events that could have motivated mitigation activities over longer time periods, while also allowing for short term influence of flooding that may open “windows of opportunity” and thus have more immediate impacts on mitigation activities.

Second, we use three variables that reflect a county’s hydrological conditions and overall level of potential flood risk to test **H3**. Our first flood risk variable measures the average annual precipitation (1991-2002) at weather stations within the county and is provided by the State Climate Office of North Carolina. The rainiest counties face a higher probability of riverine and flash floods, which could be a catalyst for local flood hazard mitigation. Given their position in the watershed, coastal counties convey floodwaters to the ocean and can suffer coastal flooding and storm surge problems due to hurricanes and Nor’easters. Thus, we expect the 20 North Carolina Coastal Area Management Act (CAMA) counties to be more likely to adopt flood hazard mitigation activities due to the higher level of flood risk (all else being equal). (CAMA is legislation passed by the North Carolina General Assembly in 1974. This legislation is applicable to all 20 coastal counties and the municipalities located within these counties. The purpose of CAMA is to protect the unique natural resources of North Carolina coastal areas.) Digital data on area of surface water bodies (such as streams, rivers, lakes, reservoirs, and estuaries) were collected from North Carolina Center for Geographic Information and Analysis. The percentage land cover of water bodies in a county is calculated with ArcGIS software; we expect a higher likelihood of mitigation for counties with a greater proportion of surface water. Unfortunately, we are unable to use proportion of land in the SFHA as a covariate, because digital flood hazard maps in the North Carolina Floodplain Mapping Program are available only back to 2008. We expect more densely populated areas to be more likely to engage in hazard mitigation due to greater benefit of flood protection accruing to more local residents. These data were collected from U.S. Census Bureau. We find a significant correlation between population and housing density (Corr[population density, housing density]= 0.9943), so we include only housing density in our analysis.

Third, we include three variables reflecting local capacity for hazard mitigation and competing priorities to test **H4** and **H5**. Data on per capita county property taxes, which is collected from NC Association of County Commissioners Budget & Tax Survey, represent local government financial resources available for hazard mitigation projects. We expect counties with greater tax revenue to be more likely to engage in flood hazard mitigation. Competing priorities, on the other hand, may crowd out hazard mitigation. The benefits of hazard mitigation are only realized after a disaster occurs and are difficult to quantify (as there is typically no counterfactual), but the costs are incurred immediately and are easily calculated. Therefore, other problems, such as control of crime and improving the quality of education, usually garner more attention than hazard mitigation projects. The pressing needs of such "here and now" issues may attract more time, money, and other resources and can crowd out hazard mitigation initiatives (Prater and Lindell 2000). We account for these other potential county policy priorities in our regression models. We use the ratio of enrolled students to instructional staff in county public school to measure local school quality (Card and Krueger 1992); these data were collected from NC Department of Public Instruction. We use the crime rate to proxy for the competing concerns over criminal activity in the county; the number of reported crimes (including murder, forcible rape, robbery, aggravated assault, burglary, larceny, and motor vehicle theft) per household was derived from NC Department of Justice. To account for the timing of competing priorities, we analyze the lag of school quality and crime rate in our regression models. We expect concern over education quality and crime control could shift attention and funding away from hazard mitigation projects, and we thus expect negative coefficients on these variables.

Lastly, we examine the influence of community characteristics on local hazard mitigation. We use the percentage of citizens with a bachelor or graduate degree, median household income, and the percentage of senior citizens to test **H6**. We expect that the likelihood of flood hazard mitigation is increasing with the level of education, all else being equal. Data on percentage of population with college degree or higher is derived from census data with missing years interpolated. Annual data on median household income for each NC County is not complete from U.S. Census. Thus, we use estimates from the Department of Housing and Urban Development (HUD), which are prepared as part of the process of updating eligible income limits for the community development program. Median household income provides a proxy for the level of individual wealth. We conjecture that wealthier communities may exhibit a greater demand for hazard mitigation, but since wealthier households are better able to afford individual mitigation measures and insurance they may put less pressure on local governments for hazard mitigation.

In his study of local adaptive capacity, Posey (2009) doesn’t include age structure among his socio-economic variables. While a community’s willingness to support mitigation activities may depend on the local severity of risk and the community’s commitment to dealing with the problem (Burby 1998), the vulnerability of elders as a group could be an important factor in overall vulnerability assessment which may increase the likelihood of local hazard mitigation. North Carolina, however, has become a popular retirement destination due to the state’s varied terrain, moderate climate, reasonable housing prices, and special tax exemptions for military and other federal employees' retirement pay. This has led to increasing numbers of migrating retirees, many of which may have limited experience with flood hazards. Thus, our expectations of the impact of proportion of senior citizens on hazard mitigation activities are ambiguous. We collected data on the senior population from U.S. Census.

Data that we are unable to collect include the proportion of minorities in the county, the extent of local political participation, and the structure of local government (i.e. presence of city manager). Our statistical model (described in the methods section below) helps to address this lack of information, to some extent; using panel data on participation, we are able to control for time-invariant, unobserved heterogeneity, which may account for some of these factors (e.g. government structure). While information on average property values is available, we expect this will be highly correlated with property tax revenue.

Since the structure of NFIP rests on a multi-jurisdictional configuration which allows for participating counties, towns, and cities, the extent and timing of enrollment in CRS for county and municipalities within the county may vary. To account for this structure, we measure the proportion of participating CRS municipalities that are nested within the county. Since the damage from flooding may occur at a large geographic scale, hazard assessment and management requires communication and coordination among the county and its municipalities. The county and municipalities can share technologies (GIS Mapping), resources (hazard mitigation personnel), and information. We expect more flood hazard mitigation activities to be undertaken where a larger proportion of nested municipalities participate due to technology spillovers and agglomeration effects (which can lower the cost of hazard mitigation).

We harbor some concerns over possible spatial dependence in our model. Spatial dependence occurs when response variables in one space are correlated with the responses in another (Anselin 1988). Spatial dependence may arise in this study because counties sharing common geographic features and unobservable flood risk factors may tend to cluster in space. If the relevant spatial dependence is ignored in estimation, the estimated coefficients could be inefficient or inconsistent, which may mislead inference and conclusions (Ward and Gleditsch 2008). Testing for spatial dependence in the probit model, however, is more difficult than for the continuous case due to the fact that neither residual nor dependent variable in the latent variable model can be observed. Recent theoretical literature discusses a generalization of Moran's I for probit models (Kelejian and Prucha 2001) but to date this test statistic has seen little application. Moreover, software packages such as ArcGIS and Geoda have not developed a tool to test spatial dependence in binary response models. In this study, we use the proportion of bordering counties that participate in CRS as a crude control for spatial dependence. Lastly, with many floodplain management workshops and conferences offered each year, more information on flood hazard mitigation, including CRS activities, becomes available for local floodplain managers over time. We explore this effect by examining the impact of the length of time that the county has been enrolled in NFIP. Summary statistics for the dataset are presented in table 3.2.

3.4 Methods

Our dependent variable, CRS participation, takes on only two values: zero and one, which indicates whether or not the county participates in the Community Rating System according to the aforementioned definition. The linear probability model is generally regarded as inappropriate, since the dependent variable takes only limited values and the error term will be heteroskedastic (Long 1997; Wooldridge 2002). As one of the Qualitative Response Models, the logit and probit models are widely used when the dependent variable takes discrete values

(Mckelvey and Zavoina 1975; Matyas 1992; Greene 2002; Wooldridge 2002). We begin with a latent variable model:

$$y_i^* = x_i'\beta + \varepsilon_i$$

where y_i^* is a latent (unobservable) variable which represents community i's propensity to adopt CRS activities (i.e., implement projects to lower flood risk); x_i is a vector of explanatory variables which are organized under the four broad categories discussed above; β is a vector of unknown parameters to be estimated, and ε_i is an unobserved random error term.

The latent variable, y_i^* , ranges from $-\infty$ to $+\infty$. Instead of observing y_i^*, we observed y_i indicating the sign of y_i^*:

$$y_i = \begin{cases} 1, & \text{if } y_i^* > 0 \\ 0, & \text{otherwise} \end{cases}$$

Therefore, the probability of participation in CRS is:

$$P(y_i = 1|\, X) = P(y_i^* > 0|X) = P(\varepsilon_i > x_i'\beta|\, X) = G(x_i'\beta)$$

When the error term has a standard normal distribution: $\varepsilon_i \sim N(0,1)$, the response probability $G(x_i'\beta)$ gives rise to the probit model:

$$G(x_i'\beta) \equiv \Phi(x_i'\beta) = \int_{-\infty}^{x_i'\beta} \phi(v)\, dv$$

where $\Phi(\cdot)$ is standard normal cumulative distribution function. When the error term has a standard logistic distribution, it gives rise to the logit model:

$$G(x_i'\beta) \equiv \Lambda(x_i'\beta) = \exp(x_i'\beta)\,/\left[1 + \exp(x_i'\beta)\right]$$

Since the logistic distribution is similar to the normal distribution (except with heavier tails), the two models produce similar effects estimates and give very similar predictions in most applications (Greene 2002). In both cases, the parameter vector (β) and associated standard errors are obtained by Maximum Likelihood Estimation (MLE).

A handy way to get the magnitude of the partial effects is to estimate average partial effects (APEs):

$$\left[\frac{\sum_{i=1}^{n} g(x_i'\hat{\beta})}{n}\right]\widehat{\beta_\iota}$$

where the APEs scale factor, $g(x_i'\hat{\beta}) = \phi(x_i'\hat{\beta})$ for the probit model and $g\left(x_i'\hat{\beta}\right) = \exp\left(x_i'\hat{\beta}\right) / [1 + \exp\left(x_i'\hat{\beta}\right)]^2$ for the logit model. If x_i is discrete, the marginal effect is computed as the difference in the estimated probabilities with $x_i = 1$ and $x_i = 0$ and other variables at their means.

Aside from the limited values of the dependent variable, our dataset has annual observations for each county from 1991 to 2002, which forms a combined time-series, cross-sectional dataset, also known as longitudinal or panel data. An advantage of panel data over the cross-sectional format is that it allows the analyst to account for cross-sectional unobserved heterogeneity. For instance, in a typical cross-sectional regression analysis, the researcher can account for observable heterogeneity using covariates; in our application, this would include county characteristics, such as property tax revenue, housing units, and population. In some cases, the covariate effects are of direct interest to test hypotheses about causation or correlation, while in others they are introduced as control variables. If, however, there are other unobserved factors influencing the counties' propensity to conduct flood hazard mitigation activities, the regression parameter estimates can be inconsistent (creating bias in parameter estimates that does not decrease or disappear as the sample size increases). For our application, local government structure and perceptions of flood hazard, as well as idiosyncratic features like history or culture, which are unobserved or unobservable, may affect CRS participation, and thus controlling for unobserved heterogeneity could be very important.

To control for unobserved heterogeneity, we consider the unobserved effects panel data model for latent dependent variable:

$$y^*_{it} = x'_{it}\,\beta + c_i + \varepsilon_{it},$$

where c_i represents an unobserved , time-invariant cross-sectional effect for unit i. Random effects and fixed effects are two approaches to estimate this model under strict exogeneity of the explanatory variables ($E(\varepsilon_{it}|x_i, c_i) = 0$). The random effects approach to estimating β involves specifying a distribution for components of the error term, c_i and ε_{it}, under the assumption that c_i and x_{it} are independent. The random effects probit model has been considered in several research papers (e.g., Bjorklund 1985; Clark 2003; Das and Arthur 1999; Gerlach and Stephan 1996; Korpi 1997; Schwarze 2003; Winkelmann and Winkelmann 1998). An alternative specification, the fixed effects approach attempts to estimate the individual c_i, or condition them out of the likelihood function. For the probit model, the fixed effects specification typically cannot be estimated due to the incidental parameters problem, which inhibits identification of fixed effect parameters. For the logit model, the fixed effects specification is only suitable when there is variability in the dependent variable at the level of the cross-section – this applies to only a small proportion of observations in our dataset.

We focus on a panel of 100 NC counties over a period of 12 years. In the unobserved effects latent variable model:

$$y^*_{it} = x'_{it}\,\beta + \epsilon_{it}, \qquad i=1,2,\ldots,100, \quad t=1,2,\ldots,12 \qquad \text{where} \quad \epsilon_{it} = c_i + \varepsilon_{it}$$

where ε_{it}~N(0,1) and $c_i|x_i$~N $(0, \sigma_c^2)$, Var(ϵ_{it})=1+σ_c^2. The importance of the unobserved effect is measured as $\rho = \frac{\sigma_c^2}{1+\sigma_c^2}$, which is the correlation between ϵ_{it} across any two time periods (Wooldrige 2002; Greene 2002). Standard statistical packages report estimated rho ($\hat{\rho}$) and its standard error along with other random effects probit parameters, which allows for straightforward testing of the presence of unobserved, time-invariant cross-sectional effects. The unobserved factor, c_i, accounts for cross-sectional, time invariant factors that influence the counties' propensity to conduct flood hazard mitigation activities. Our specification does not, however, account for time shocks that may affect local hazard mitigation decisions. Examples might include changes in government personnel, or the occurrence of a major hurricane event that doesn't directly impact the area of interest. Thus a strong argument supports the inclusion of time effects in the unobserved effects probit model (Wooldrige 2002, page 484). We use time dummies to control for unobserved temporal effects. The likelihood function for random effects probit model can be found in Wooldridge 2002 (Chapter 15), along with formulas for the calculation of APEs. An alternative to random effects probit is random effects logit, which can provide consistent estimates of β without the assumption about the relationship between c_i and x_{it}. There are, however, no simple estimators available for this model (Woodridge 2002, page 490), necessitating use of random effects probit.

The issue of endogeneity arises whenever an explanatory variable is correlated with the error term, either because of the omitted variables, measurement error, or simultaneity (Wooldridge 2002). In our study, we are concerned about endogeniety bias due to simultaneity: some explanatory variables are jointly determined with the dependent variable. It is helpful to outline a heuristic framework in order to provide the background for the specifications:

$$CRS\_Comm_{it} = \alpha_t + \beta_1 prop\_damage_{it} + \beta'_2 X_{it} + \epsilon_{\mathrm{it}}$$

where X_{it} is a vector including all other covariates in Table 3.2. Simultaneity in property damage (for single-year and two-year lags) can arise because property damage stemming from floods is influenced by lagged CRS participation decisions. Consider the equation:

$$prop\_damage_{it} = \gamma_t + \delta_1 CRS\_Comm_{t-1} + u_{it}$$

If $\delta_1 \neq 0$, the exogeneity assumptions ($E(\varepsilon_{it}|x_{it}) = 0$) will be violated. If $\delta_1 < 0$ (as would be expected), the regression estimate of β_1 will be attenuated (downward biased) and inconsistent, and regression estimates for covariates that are correlated with past property damage may also be biased.

One might also harbor concern over the flood events variable, but it depends how flood events is defined. If defined as water levels reaching flood stage, this variable should not be endogenous. If, however, designation of a flood event is triggered by occurrence of property damage or other factors that can be influenced by mitigation, then the variable could be endogenous. Our flood events variable is derived from National Weather Service (NWS) reports. The NWS receives storm information including flood events from: county, state and federal emergency management officials; local law enforcement officials; skywarn spotters; NWS damage surveys; newspaper clipping services; the insurance industry; and the general public. As such, there is no clear and consistent definition of flood events. While correcting for explanatory variables that are not strictly exogenous is difficult in nonlinear models, Wooldridge (2002) suggests an easy test of strict exogeneity. Wooldridge's test involves adding future realizations of the potential endogenous regressor to the estimating equation. Under the null hypothesis of strict exogeneity these regressors should be statistically insignificant. Undertaking this test with flood events, we find that coefficients on future realizations are all insignificant, which provides some justification for the strict exogeneity assumption. We thus estimate two versions of the regression model, one with flood events as the experience variable and the other with property damage. To the extent that parameter estimates for other covariates are similar across the two models, we express confidence in the results that use property damage as an experience measure.

Nonetheless, we expect that the parameters on property damage will be downward biased (by an unknown magnitude).

3.5 Results

We use the random effects probit model in two specifications – Model 1 (flood events specification) and Model 2 (flood damage specification). Both models are estimated using STATA statistic analysis software. The estimation results for each of the models with Average Partial Effects (APEs) are shown in Table 3.3. Concerned with endogeneity of lagged property damage, we focus primary attention on the results in Model 1. The signs for most of the covariate parameters, which indicate the direction of impact on probability of participation in CRS, are consistent across both models. The exception is elapsed years since joining NFIP (*NFIP_Year*), which is estimated to have a negative effect in the Model 1 but a positive effect in the Model 2 (both of which are statistically insignificant). Since the probit models use maximum likelihood estimates derived from an iterative process (instead of minimizing the sum of squared errors), the standard R-square measure does not apply. McFadden (1974) suggests the measure $1 - L_{ur}/L_0$ (pseudo R-squared), where L_{ur} is the value of the log-likelihood function for the estimated model, and $L_0$is the value of log-likelihood function for the model with only an intercept term. The pseudo R-squared ranges from 0 to 1 with higher values indicating better fit. Both pseudo R-squares indicate good fit for the maximum likelihood models, with pseudo R-sq=42.3% for the Model 1 and pseudo R-sq=41.8% for the for the Model 2. The number of statistically significant covariates decreases from ten to nine when we move from Model 1 to Model 2. To account for unobserved heterogeneity, the random effects probit model is employed under the assumption of strict exogeneity of the explanatory variables. The statistically significant rho parameter($\hat{\rho} \approx 0.958$) indicates the existence of an unobserved time invariant effect at the cross-sectional level. Therefore, the random effects model is preferred to a pooled probit specification.

We consider first the impact of flood experience on CRS participation. In Table 3.3, the pre-CRS flood event variable is statistically significant and positive in Model 1, suggesting that an additional flood from 1980-1989 (before the establishment of CRS) *increases* likelihood of participating in CRS by 6.56%. Short term flood events, however, appear to have no statistically significant impact on CRS participation. This result is robust to different lag lengths for flood events (i.e. three or four years – results available upon request). Results from Model 2 are statistically insignificant for pre-CRS and one- and two-year lagged property damage. For the lag results, the lack of significance could be expected given attenuation of the estimated coefficients. Thus, we find some support for historical flood experience motivating participation in CRS, but no support for initiation of CRS activities in the short term during windows of opportunity that follow storm events. The lack of support for the windows of opportunity hypothesis in our case may be an artifact of our focus on counties as the level of analysis (as hazard mitigation could be occurring at the level of nested municipalities) and may reflect a lack of clarity regarding responsibility for floodplain management (Godschalk, Brody and Burby 2003). Long term experience with flood events, however, appears to strongly encourage local hazard mitigation activities at the county level.

We account for potential variability in flood risk across counties with a number of covariates –average annual precipitation (from 1991-2002), a dummy variable for CAMA counties (meant to capture additional risk associated with downstream riparian flooding and storm surge), and water body coverage (measured as percentage of total county area). Our expectations are that higher risk factors will be associated with greater likelihood of participation. Results indicate that counties with greater average rainfall and a greater proportion of water body are more likely to participate in CRS. Focusing on Model 1, a one-inch increase in annual precipitation increases participation likelihood by 0.16% and a one percent increase in the proportion of water body in a county increases the likelihood of CRS participation by 1.82%. The estimates from Model 2 are roughly equivalent. From an economic and public policy perspective, these results are encouraging, as they suggest that flood hazard mitigation is more likely to occur in areas that face greater flood risk.

Surprisingly, the marginal effect for CAMA counties is statistically significant and *negative* in Tables 5, suggesting that CAMA counties are less likely to participate in CRS (all else being equal). The average partial effects are -12.80% in Model 1 and -10.19% in Model 2. Coastal counties are exposed to storm surge, coastal flooding associated with upstream rainfall and coastal storms, and erosion hazards. In North Carolina, under the Coastal Area Management Act (CAMA) of 1974, all 20 counties classified as 'coastal' have been required to prepare local land use plans that include provisions for storm hazard mitigation, post-disaster recovery, and evacuation (Beatley, et al. 2002).

Under CRS Activity *430 Higher Regulatory Standards*, state-mandated regulatory standards (SMS), which are included in NC CAMA regulations, are credited up to 45 CRS points. In North Carolina, only coastal counties receive SMS credit associated with CAMA regulations. To explore whether coastal counties are receiving CRS credit for higher mandated regulatory standards, we analyze CRS point data from 2002 – 2008. (Detailed CRS points data are not currently available for the time period 1991 – 2001.) A two sample t-test reveals that the mean of CRS points for *Activity area 430* is significantly greater for participating CAMA counties (t = -1.863, $p\text{-}value < 0.03$, df = 123). We interpret CAMA CRS counties' higher

Activity 430 points as indicating a rather limited impact of the mandated CAMA program on county-level flood hazard mitigation (or at least a failure on the part of county officials to translate hazard mitigation into flood insurance premium discounts by applying for CRS credit). Our data suggest that, aside from the mandated activities, CAMA counties are not as active in hazard mitigation (as reflected in CRS participation) when we control for other factors (such as flood experience, risk factors, and financial capacity). It is possible, however, that coastal flood hazard mitigation is occurring at the level of waterfront towns and cities in CAMA counties, rather than at the county jurisdiction. The multi-jurisdictional scale of NFIP and CRS makes this possible. As of 2010, 37 municipalities (38.9%) within the CAMA counties were participating in CRS on their own behalf – most of these 37 towns and cities are waterfront coastal communities (including CAMA municipalities located on the oceanfront, estuaries, and rivers). The fact that many coastal counties in North Carolina have limited commercial and residential development, except along river, estuary, and oceanfront shorelines could reasonably explain such mitigation patterns. Mitigation activities across the various local jurisdictions remain an important area for future research.

The estimated average partial effect of per capita property tax levy exhibits a positive and statistically significant sign, which abides our expectations that financial capacity would increase the likelihood of the policy adoption & implementation. Results of the preferred Model 1 indicate that one hundred dollar increase in average property tax per capita increases the likelihood of CRS participation by 6.23%. Similar results are obtained in Model 2 (6.17%). These findings imply that flood hazard mitigation is more likely to occur in wealthier districts with greater tax revenue and that poorer districts with less financial capacity may be more vulnerable to flood hazard. In addition, wealthier districts might also be expected to have more valuable building stock and thus more incentive to protect it.

For competing local public policy priorities, we use student-teacher ratio to account for local public school quality and crimes per household to account for public safety. We expect school quality and crime could be strong competitors with hazard mitigation projects for limited local financial resources. The estimated coefficients for lag(student-teacher ratio) exhibit an unexpected negative sign, but they are not statistically significant. We also used (lagged) local education expenditures per student as an alternative proxy for school quality and found similarly insignificant results. The estimated coefficients for crimes per household exhibit a positive sign, but are also not significant. A better proxy for public safety would be the local budget for public safety or police protection (for which data are unavailable). The statistically significant and positive coefficient on *Hu_density* indicates that more densely developed counties are more likely to participate in CRS. According to the result of Model 1, increasing houses per square mile by one unit increases the probability of participation by 0.14%. This could indicate a pure benefit effect (as more homes exposed to risk increases the benefit of mitigation), but could also reflect greater local government financial capacity (tax base).

Holding flood experience, hydrological risk factors, and level of financial resources constant, the influence of median household income on likelihood of participation in CRS is positive in both models, but neither coefficient is statistically significant. The percentage of senior citizens in a community has significant and negative impact on likelihood of participation in CRS. In Model 1, the probability of participation decreases 1.66% for a 1% increase in proportion of senior citizens; we find similar results for Model 2. We expect that this result may be driven by migration patterns of retirees (Deller 1995). Having a temperate climate, varied natural resources, low cost of living, and favorable tax treatment for former federal employees, North Carolina has witnessed a tremendous influx of migrating retirees. Due to scenic beauty, hazard-prone areas tend to be primary destinations for retiree migration. The potential increase in tax base is particularly attractive to local governments, and many of the migrant retirees may be uninformed about potential flood hazards. This is a plausible explanation for the negative effect of senior population, and suggests that targeted information campaign and education initiatives could be effective at improving flood hazard mitigation in some areas. Unlike the studies of Posey (2009) and Brody, et al. (2009), our random effect probit model finds a *negative* and statistically significant impact for proportion of college (and higher degree) educated citizens attributed to CRS participation. Our prior expectations were that counties with more educated residents might have higher demand for mitigation projects that can lower flood damage. The negative result could be an artifact of our research design, as participation in wealthier counties may be occurring at the municipality level (for which data are currently unavailable). We also note that our education measure is derived from linear interpolation using U.S. decadal Census data (1990, 2000). Thus, this unexpected result could be due to systematic measurement error. Nonetheless, this result deserves further exploration in future research.

For each model, the estimated coefficient for *CRS_Muni* is positive and statistically significant at 5% level. Increasing the proportion of participating municipalities within a county by one percent, the county participation probability increases by 1.37% in the Model 1 (1.38% in Model 2). We construe this as evidence of strong agglomeration and spillover effects in local hazard mitigation. Since hazard identification, management, and mitigation requires specialized equipment and expertise, more involvement by nested towns and cities could increase the likelihood of county participation. Causation could also go in the other direction. We used the proportion of CRS neighbor counties to partially account for spatial dependence. The estimated impact is not statistically significant in either model. Lastly, we find that the number of years since joining regular NFIP has contradicting signs in the two models, but insignificant impact on likelihood of participating in CRS.

3.6 Conclusions and Policy Implications

While the dynamics of weather patterns play an important role in the recent growth of damaging floods in the U.S., intensive development in floodplains and extensive population growth in low lying and coastal areas have increased human beings' exposure to flood hazard. The communities that engage in hazard mitigation planning and management activities are less prone to flood hazard and recover faster from disaster than those communities which do not (NOAA 2010). The CRS rewards communities for undertaking mitigation activities beyond the minimum requirements of NFIP with reduced flood insurance premiums. Most of the rewarded activities, such as stricter regulation of building codes, relocation of repetitive loss structures, and education and outreach, can reduce injuries, deaths, and damages and increase the communities' awareness of and resilience to flood hazards. Since CRS uses standardized quantitative measures for representing local hazard mitigation activities, it provides an excellent source of information for empirical analysis of community hazard mitigation decisions.

Evidence of the effectiveness of CRS has been provided in a study by Brody, et al. (2007), which indicates that flood damage can be decreased by approximately 15% by increasing CRS rating by 1unit. Participation in CRS, however, is as low as five percent of eligible NFIP communities nationwide. Given substantial variability in local physical, political, and social conditions, the existing voluntary framework for local hazard mitigation may have advantages in allowing locals to identify "low-hanging fruit" while tailoring their hazard mitigation plans to local factors and concerns. In the flood hazard management network, disaster assistance and flood insurance are handled at the federal level due to the existence of greater financial capacity and the larger policy base needed for risk pooling; state governments are to provide policy guidance, technical assistance, and integration of floodplain management issues within a state; local government, however, is the locus of comprehensive land use planning, including floodplain management, within their jurisdictions. What drives community participation in CRS within the current voluntary framework is an important policy question.

Our empirical models explore the impact of previous flood events and flood related property damage over both the long (pre-CRS) and short term (previous one and two years). We find evidence that flood events can influence hazard mitigation over longer time periods, but we do not find evidence in support of shorter term impacts of flood events. A null result for one-year lag could be expected, as local resources and personnel may be focused on recovery, but the null for short term impacts is robust to different window lengths (e.g., three- and four-year). The effects found for historical flooding may indicate that certain communities that had have experienced hazards were more likely to enroll in CRS at the program inception, and those communities continue to obtain credits for hazard mitigation activities, while other communities are more resistant to voluntary hazard mitigation and remain unconvinced of the potential benefits even in the wake of flood events.

Prater and Lindell (2000) argue that the immediate aftermath of hazard events can open a "window of opportunity" as public sentiments shift to support of hazard mitigation, but this window soon closes as attention shifts to other pertinent issues, such as job creation, school quality, transportation, and crime. Our results do not support the hypothesis that windows of opportunity immediately following disasters are important determinants of flood hazard mitigation (at least as measured by CRS). There are a number of possible explanations for this. The effects of recent disaster events may be attenuated by continual federal disaster assistance and subsidies for rebuilding in high-risk areas. Federal and state agencies should seek to provide a stronger framework for grants-in-aid, low interest loans, and technical assistance to help build resilient communities before disasters instead of focusing attention on post-disaster rebuilding efforts. Moreover, the description of flood hazard mitigation activities in the *CRS Coordinator's Manual* focuses primarily on the process used to assign mitigation points, with less attention paid to the potential local benefits of mitigation activities, in terms of property damage avoided and lives saved. While these factors could be very difficult to quantify from a general standpoint, examples or brief case studies could be useful to illustrate the benefits of flood risk management. FEMA and state agencies could take a more active role in demonstrating successful hazard mitigation programs after local flood events, especially focusing on differences between CRS and non-CRS participants. Cases of successful hazard mitigation could be publicized in the wake of catastrophic events, with the goal of transferring effective mitigation strategies to other hazard-prone NFIP communities. The real limitation in such a demonstration is establishing an accurate counterfactual – what would flood impacts have been in the absence of existing hazard mitigation projects. Searching for appropriate comparison groups or designing simulations that measure the effectiveness of mitigation could be useful strategies. These information conduits could help local governments understand and visualize the potential benefits of the flood hazard mitigation projects, which could strengthen their own flood protection programs. Lastly, the lack of empirical support for the window of opportunity hypothesis may be an artifact of our research design, as we only focus on the county level. Future research should incorporate the multi-jurisdictional structure of CRS.

Our results suggest that physical risk factors play a significant role in the likelihood of CRS participation, as does the density of development. We find higher water body percentage of total land area and greater average rainfall within a county each significantly increases the likelihood of CRS participation. This is encouraging, as it suggests that voluntary adoption of hazard mitigation activities is more likely to occur in areas that face greater risk, as well as in areas that are more densely developed. Given this evidence in support of systematic hazard assessment on the part of local government, community assistance programs that emphasize scientific applications in estimation of potential flood losses could increase the adoption of flood hazard mitigation in vulnerable areas. In 1997, FEMA developed a science-based software tool for estimating flood damages – HAZUS – which can facilitate local communities' analysis and mitigation of flood damage. Limited sources of input data, however, degrade the ability of communities to use HAZUS for hazard assessment (ASFPM 2007). Recommendations include enhancing data inventory and strengthening loss simulation models (Chang, Peacock and French 2008; Davidson, Schneider and Muthukumar 2008). FEMA and state governments could encourage the use of HAZUS and similar hazard assessment technology through aggressive advertising and additional technical assistance.

Our results suggest that, holding other factors constant, the likelihood of mitigation is lower in coastal counties, which face greater flood risk due to downstream riparian flooding and storm surge. The Coastal Zone Management Act (CZMA) was enacted in 1972 to encourage coastal states to develop comprehensive programs to manage competing uses of coastal resources. Incorporated with CZMA, the NC Coastal Area Management Act (CAMA) regulations apply to coastal counties and mandate setback rules and building code standards to protect coastal communities from erosion, wind, and storm surge. CRS provides limited credit to coastal counties for state-mandated regulatory standards under CAMA, and our results indicate the among CRS participants, point totals in for this activity area are higher for coastal counties relative to other counties. Nonetheless, the credit awarded (45 points total) is very small and potentially inconsequential in relation to the total points necessary to decrease CRS score (500 points) to receive additional discount on flood insurance premiums. Examining the raw data, however, we find that 34 of the 60 (56.7%) waterfront municipalities participated in CRS as of 2010, and a smaller proportion of the overall municipalities in the CAMA counties – 35.8% – participate in CRS. Thus, it appears that flood hazard mitigation may be occurring at a finer scale (where development is more focused) along the NC coast.

Like CZMA, federal leadership to build the strong state capacity could be an efficient way to achieve more commitment in local level mitigation. Experience suggests that effective local management occurs in the presence of strong state floodplain management programs. Burby (2005) finds evidence that insured losses to residential property from natural disaster are significantly reduced if the state mandates local comprehensive plans with hazard mitigation elements (which are currently optional in some U.S. states). State programs could go further to achieve more initiation of local mitigation projects through state mandates of some CRS activities, such as public outreach about coastal hazards. Also, similar to NFIP, the state could provide direct technical assistance to local governments in initiation of CRS activities, training of local floodplain mangers, and managing or assisting with hazard mitigation.

We find that education level and age structure are important factors in local hazard mitigation adoption and implementation. Counter to expectations, we estimate a negative effect of education attainment on the likelihood of CRS participation. This is a surprising result that requires further exploration. We find evidence that the proportion of senior citizens within a county has a negative influence on the likelihood of CRS participation. While elderly people may suffer more injuries and loss of life in disasters than younger population, with greater and more diverse life experiences and social support, elders exhibit greater resilience to the effects of disaster (Tierney, Lindell and Perry 2001), which may explain this result. In addition, by offering significant tax advantages for military and other federal retirees, low cost of living, and attractive recreation opportunities, North Carolina has become a primary destination state for migrating retirees. Data from the U.S. Census (He and Schachlter 2003) indicates that North Carolina witnessed a 22% senior net migration rate from 1995 to 2000, which ranks 5th in U.S. during this period. While we do not observe senior migration rates in our data, age structure of the community could reflect these retiree migration patterns. Migrating seniors can induce significant potential for economic development in scenic, rural communities, and local elected officials may focus more on this development opportunity (which can create significant economic benefits and a larger tax base) and less on potential changes in vulnerability to natural hazards that can be associated with rapid economic development. Migrating retirees from outside the state may be less aware and knowledgeable of flood hazards and thus could put less pressure on local government to engage in flood hazard mitigation. As the U.S. population continues to age, it becomes increasingly important to consider elders in pre-disaster mitigation planning. Our result has implications for targeting of information and outreach programs which could be conveyed through public meetings, media, or other venues where senior members of the communities could be well represented.

Holding risk and population factors constant, the average county property tax levy has a positive and statistically significant impact on CRS participation. This indicates that financial capacity is an important determinant of flood hazard mitigation (supporting the findings of Prater and Lindell (2002)), and suggests that vulnerability may be higher in poorer communities with lower property tax revenue. The findings would support the establishment of low-interest loan programs or state grant-in-aid programs targeting counties without adequate resources, high risk factors, and high potential for floodplain development. Subsidized interest rates and outright grants could be economically justified in terms of foregone disaster aid and lower business interruption (resulting in lower tax revenue losses).

In a recent report, NOAA Community Service Center (CSC) (2010) summarizes a number of factors that contribute to specific risk and resilience-related behavior derived from a series of structured interviews with local planners. This report concludes that barriers to hazard planning include competing priorities, among other factors. We do not find supporting evidence of competing priorities on diminished CRS participation, as the effect of lagged crime rates and student-teacher ratios are not statistically significant in our regression models. There is much greater variability in crime rates at the municipal (i.e. sub-county) level, which may explain the lack of significance of this covariate in our models. Future research should also attempt to refine our approach (with better data) and explore the extent to which other local problems (transportation and economic development) crowd out investments in hazard mitigation.

CRS community divisions rest on a multi-jurisdictional scale which includes towns, cities, and counties. Therefore, the county and nested municipalities may exhibit divergent flood-loss reduction efforts with separate floodplain management ordinance and regulations. In their study, Brody, et al. (2009) use population-adjusted measures of CRS activities, CRS score, and community-level covariates to account for nested municipalities and the county itself in their county-scale analysis. They find that local governments adjust their policies to improve risk management efforts after flooding events. Our analysis is a contribution to the limited quantitative literature exploring the influence of flood experience, hydrological risk, financial capacity, and socio-economic factors on local hazard mitigation decisions. We focus on the CRS participation decision and only on the county level, primarily because data on covariates are not readily available at lower jurisdiction levels. We find evidence of agglomeration and spillover effects among the various jurisdiction levels, as the probability of county participation is augmented by the presence of nested participating cities and towns; the magnitude of this effect is quite large at 1.37% for just a one percent increase in the proportion of participating nested municipalities. A more detailed and thorough analysis of the relationship between hazard mitigation at the level of counties and cities & towns remains an important area for future research.

Table 3.1: Data Description

Variable	Description
Dependent Variable	
CRS_dummy	CRS participation dummy (1,0) (1991-2002)
Flood Experiences Variables	
PreCRS_floods	Total number of floods in county prior to CRS (1980 to 1989)
PreCRS_damage	Total amount of flood-related property damage in county prior to CRS (1980 to 1989) (in millions of dollars -year 2000 inflation adjusted dollars)
Lag_1_floods	Total number of flood events in previous year in county (1990-2001)
Lag_1_damage	Total amount of flood-related property damage in previous year in county (1990-2001) (in millions of dollars -year 2000 inflation adjusted dollars)
Lag_2_floods	Total number of flood events in previous two years in county (1989-2000)
Lag_2_damage	Total amount of flood-related property damage in previous two years in county (in millions of dollars - year 2000 inflation adjusted dollars) (1989-2000)
Environmental and Risk Control Variables	
Precipitation	Average annual precipitation – collected from weather stations in each county (inches) (1991-2002)
CAMA	Dummy variable, equal one for CAMA county, equal zero otherwise.
Water_precentage	Percentage of county area covered by surface waters (streams and rivers, lakes, reservoirs, and shorelines) (%)
Resources Variables	
Avg_Tax	Property tax levy per capita in each county (in thousand dollars - year 2000 inflation adjusted dollars) (1991-2002)
Student_Teacher	Students and teachers ratio in public schools in previous year (1990-2001)
Crime_density	Number of reported crimes per household in previous year (1990-2001)
Hu_density	Number of housing units per square mile (1991-2002)
Social Variables	
Income	Median household Income (in thousand dollars-year 2000 inflation adjusted dollars) (1991-2002)
Senior	Percentage of senior citizens (65 years and over) out of total population (%) (1991-2002)
College	Percentage of residents with college degree or higher (%) (1991-2002)
CRS_muni	Percentage of CRS municipalities out of total number of municipalities nested in each county (%) (1991-2002)
CRS_neighbor	Percentage of neighbored CRS counties out of total number of neighbored counties (%) (1991-2002)
NFIP_year	Number of years since the county joined regular program of NFIP (1991-2002)

Table 3.2: Data Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
CRS_dummy	0.170	0.376	0	1
PreCRS_floods	1.940	1.038	1	6
PreCRS_damage	0.086	0.504	0.001	5.001
Lag_1_floods	0.353	0.629	0	5
Lag_1_damage	0.113	1.115	0	31.100
Lag_2_floods	0.387	0.674	0	4
Lag_2_damage	0.115	1.128	0	31.100
Precipitation	47.551	6.041	37.266	71.607
Water_percentage	5.225	12.325	0	69.280
CAMA	0.200	0.400	0	1
Avg_Tax	0.352	0.120	0.126	0.892
Student_Teacher	14.431	1.182	8.756	20.278
Crime_density	0.102	0.057	0	0.376
Hu_density	77.196	103.171	4.806	751.182
Income	40.468	8.297	22.499	68.248
Senior	14.514	3.492	5.562	26.262
College	14.944	7.522	6.770	51.989
CRS_muni	8.821	20.717	0	100
CRS_neighbor	14.644	16.212	0	75
NFIP_year	9.738	6.116	0	29

Table 3.3 Radom Effects Probit Estimation Results

Models	Model 1		Model 2	
Variables	*Estimated Coeff. (Standard Error)*	*APEs*	*Estimated Coeff. (Standard Error)*	*APEs*
PreCRS_floods	0.858* (0.502)	0.0656	Not Included	
Lag_1_floods	0.187 (0.264)	0.0154		
Lag_2_floods	-0.382 (0.317)	-0.0314		
PreCRS_damage	Not Included		1.185 (1.018)	0.0964
Lag_1_damage			0.093 (0.129)	0.0076
Lag_2_damage			-0.135 (0.206)	-0.0111
Precipitation	0.233** (0.090)	0.0016	(0.251)** (0.090)	0.0012
Water_percentage	0.241** (0.069)	0.0182	0.239** (0.101)	0.0179
CAMA	-7924** (2.074)	-0.1280	-6.040** (2.168)	-0.1019
Avg_Tax	9.287** (3.989)	0.6027	9.753** (3.948)	0.6172
Student_Teacher	-0.321 (0.227)	-0.0167	-0.261 (0.218)	-0.0158
Crime_density	7.386 (7.706)	0.5976	4.613 (7.847)	0.3750
Hu_density	0.018** (0.009)	0.0014	0.018** (0.008)	0.0013
Income	0.032 (0.084)	0.0026	0.037 (0.077)	0.0029
Senior	-0.371** (0.157)	-0.0166	-0.352** (0.166)	-0.0167
College	-0.187* (0.096)	-0.0128	-0.141** (0.071)	-0.0103
CRS_muni	0.189** (0.028)	0.0137	0.192** (0.030)	0.0138
CRS_neighbor	-0.027 (0.024)	-0.0022	-0.020 (0.025)	-0.0017
NFIP_year	-0.007 (0.090)	-0.0006	0.003 (0.098)	0.0003
Time Dummies	Included		Included	
Constant	-13.457** (7.519)	–	-15.690** (6.335)	–
Log-likelihood	-98.623		-99.500	
pseudo R-squared	0.423		0.418	
$\hat{\rho}$	0.958		0.958	
Obs	1189		1189	

Note: * means that the estimation is significant at 10%; ** means that the estimation is significant at 5%.

Figure 3.1: North Carolina Counties' Participation in the Community Rating System of NFIP.

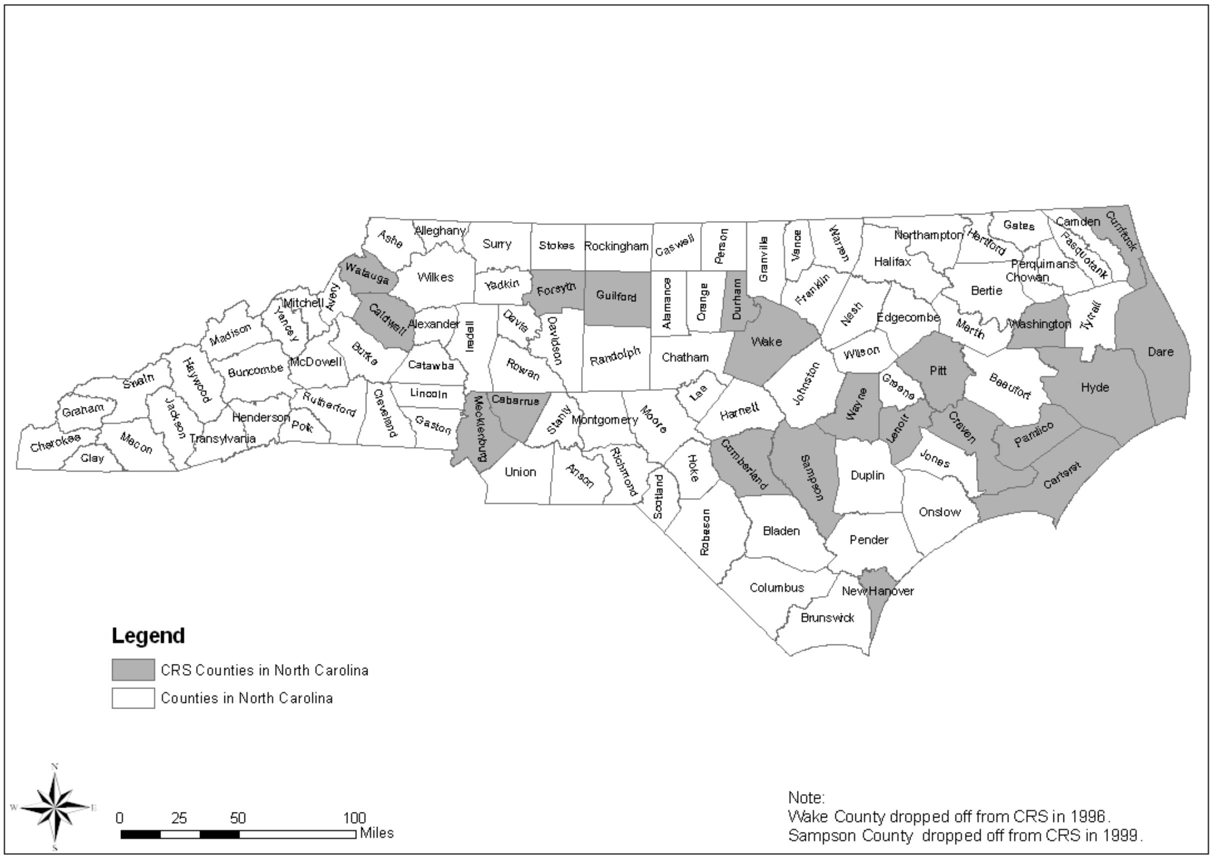
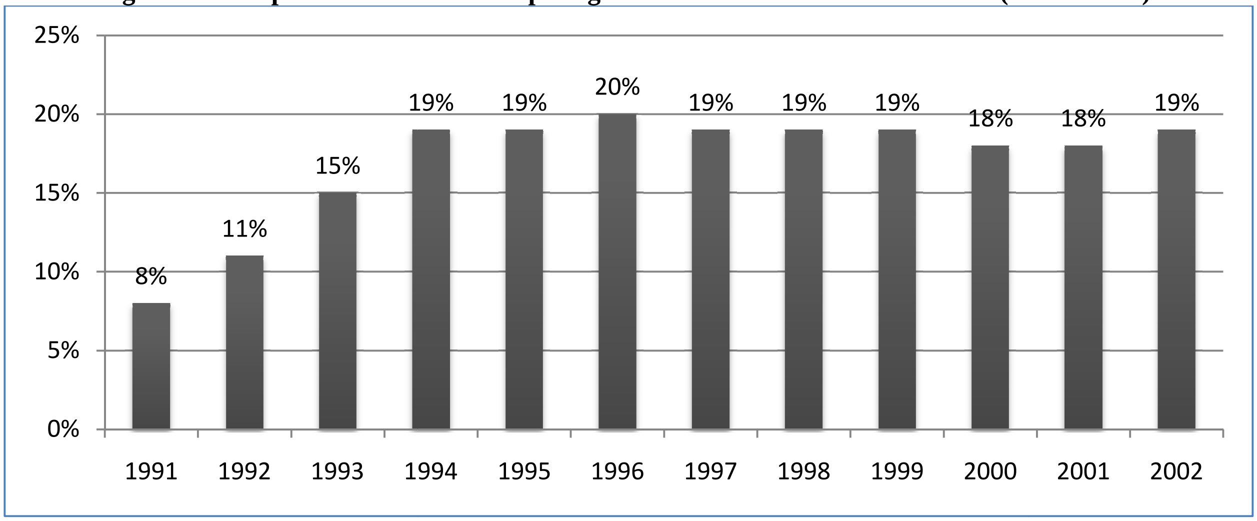


Figure 3.2: Proportion of CRS Participating NC Counties over the Time Series (1991 – 2002)



Chapter 4: Evaluation of the Community Rating System of National Flood Insurance Program – An Application of Propensity Score Matching

4.1 Introduction

As a part of floodplain management and flood loss reduction programs, the National Flood Insurance Program (NFIP) has been successful in helping flood victims get back on their feet. Federal Emergency Management Agency (FEMA) estimates that over 940,000 claims, totaling approximately $14 billion, have been paid from 1978 to 2004 and flood damage is reduced by nearly $1 billion a year as a result of the NFIP floodplain management regulations for new construction (FEMA 2007). Prior studies have identified potential improvements to the program, such as more timely updates to Flood Insurance Rate Maps (FIRMs), the alleviation of repetitive losses for some parcels, and increasing premiums for pre-FIRM and other policyholders so that they more accurately reflect risk. In order to reduce flood loss through community-level mitigation projects, facilitate accurate insurance rating, and promote the public’s awareness of flood hazard and insurance, the Community Rating System (CRS) was instituted by Federal Insurance Administration (FIA) as a voluntary program for NFIP-participating communities in 1990. CRS credits 18 community floodplain management activities in four broad categories: (1) public information; (2) flood mapping and regulation; (3) flood damage reduction; and (4) flood preparedness. FEMA classifies the portfolio of community flood management practices on a ten point scale, reflecting the overall level of mitigation. The CRS classification determines premium discounts for insurance purchases under the NFIP. Discounts range from five to 45 percent. By offering CRS credit for updating of flood risk data, information on flood hazard may become more accurate over time, leading to better delineation the flood hazard areas within a community. The CRS rewards communities for undertaking mitigation activities beyond the minimum requirements of NFIP with reduced flood insurance premiums. Most of the rewarded activities, such as stricter regulation of building codes, relocation of repetitive loss properties, and education and outreach can reduce injuries, deaths, and damages and increase the communities' resilience to flood hazards.

In 2007, the CRS Task Force and FEMA revised the 1987 goals, which had been the foundation of the CRS since its inception. The new, 2007, goals are to (1) reduce flood damage to insurable property; (2) strengthen and support the insurance aspects of the NFIP; (3) encourage a comprehensive approach to floodplain management. Although the CRS has been recognized as a successful and mature program within the NFIP, FEMA wants to improve the public contribution made by the CRS. To do so, it is critical to assess the performance of the CRS and to develop innovative ways to enhance its operations and outcomes. In order to enhance the operation of CRS and encouraging the participation of the eligible communities, society must understand the effectiveness of CRS flood mitigation activities before it can decide whether to allocate management resources. However, there is few, quantitatively, research modeling evaluation of the CRS in term of its impact on reducing flood damage, which the study in this section will cover. This chapter uses propensity score methods to estimate the impact of the CRS on the property damage protection.

The objective of evaluating voluntary programs is to compare the two outcomes from the same unit when it is treated and not treated (Imbens and Wooldridge 2009). The true performance of CRS can be determined if one compares the same group of outcomes in term of average property damage reduction in the flood events having been managed with their untreated selves. However, it is impossible to observe what would have happened to CRS participants in absence of the participating into the CRS, which is called the counterfactual (Smith and Todd

2005). Meanwhile, the data or budgetary constraints necessitate using observational data to evaluate the effect of programs. However, underlying factors may affect the individual decision make regard to enter the program. In other words, there is self-selection into CRS: it is possible to observe the communities with higher levels of mitigation activities to have also more loss from a flood event. Therefore, studies conducted using endogenously stratified samples may benefit from decrease data collection costs but inference from these samples must account for non-random sample selection bias.

The candidate communities participate CRS on the basis of eligibility criteria (i.e. must be a NFIP community with minimum 500 CRS points). Because the treatment assignment is nonignorable (i.e. the decision to participate may not be random and may correlate with the outcomes), the self-selection of participants imposes a challenge on the evaluation. The counties who choose to enroll in the CRS are different from those who choose not to enroll. These differences may invalidate causal comparisons of property damage reduction by local mitigation projects, possibly even after adjusting for observed covariates. Therefore, comparisons of outcome (i.e. property damage reduction) between CRS counties and non-CRS counties may have less to do with the program effects and more to do with other differences between the two groups. The primary objective of this chapter is to use the propensity score matching (PSM) methods to correct sample selection bias due to observable differences between the CRS participants and comparison groups. The methodology in this chapter makes important advances in understanding how to measure and conceptualize the performance of a mitigation program as it applied to reducing the adverse effects of flooding. The study also yields insights into the influences on the performance evaluation of the mitigation plan for other natural disaster such as hurricanes, fire, and earthquakes.

The following section presents on using challenge in the assessment of the treatment effect of CRS in a nonexperimental design. It will become a starting point to review the preliminary concepts and introduce more advanced approaches. In section 3, we describe the strategies for employing PSM to evaluate treatment effect in nonexperimental study. Section 4 describes the propensity score analysis with nonparametric regression. Section 5 presents the calculation of the average treatment effect which we employ to study CRS performance. Section 6 described the application of difference-in-difference estimator for panel data structure. Finally, section 7 concludes the chapter.

4.2 Experimental Studies and Observational Studies

In the evaluation of treatment effect, we have two outcomes[1], Y_n , for every unit, n. One is the value associate with treated unit, $Y_n(1)$, and other is the value associate with nontreated unit, $Y_n(0)$. We use T_n as a dichotomous variable indicating treatment (i.e. participation in CRS in our case), $T_n = 1$, or nontreatment, $T_n = 0$. The traditional experimental work assigns the units to treatment randomly. The treatment and control groups are drawn from the same population (i.e. $T_n \perp$ [2]$Y_n(1), Y_n(0)$) (Dehejia and Wahba1999). Therefore, measure the treatment effect, $Y_n(1) - Y_n(0)$, for same unit at same time. In the randomized experiments, we can measure the mean impact for participation by $E[Y_n(1) - Y_n(0)]$. $E(\cdot)$ denotes expectation in the population.

In the observational study, the treatment and comparison groups are often drawn from different populations. Since we can only observe $Y_n(1)$ or $Y_n(0)$ but never both, it is challenge to measure the treatment effect, $Y_n(1) - Y_n(0)$, for same unit at same time. The treatment effect that we are interested in is Average Treatment Effect for Treated (ATT) which can be

[1] In our application, the outcome is the average property damage in flood events.

[2] where "$\perp$" denotes independence

represented by $ATT = E(Y_{n1}|T_n = 1) - E(Y_{n0}|T_n = 1)$. Since Y_{n0} (no treated outcome for treated unit) are not observable for treated unite, Rubin (1974) formulated an approach to analysis the causal effects in observational studies:

$$ATT = E\{E(Y_n|X_n, T_n = 1) - E(Y_n|X_n, T_n = 0)|T_n = 1\} \qquad (1)$$

where X_n is a group of observable covariate which is related to the distribution of both Y_n andT_n. In order to construct the unbiased estimation for the ATT, Rosenbaum and Rubin (1983) impose two assumptions: (1) *ignorable assumption*: $(Y_n(1), Y_n(0)) \perp T_n|X_n$ (i.e. there is no difference between the groups assigned to treatment and control with conditioning on observable covariates, X_n). (2) *overlap assumption*: $0 < P(T_n = 1|X_n) < 1$ (i.e. for a setting of the covariates X_n, there is a chance of having units in both the non-treatment and treatment groups.) Ignorable assumption and overlap assumption together are called *strong ignorability* (Wooldrige 2002 page 910).

With high dimensional X_n, it is difficult to estimate equation (1)[3]. Instead of conditioning on X_n, Rosenbaum and Rubin (1983) recommend estimating each unit's propensity to receive a binary treatment as a function of observable factors. Then, matching unites with similar propensity score can reduce the problem of dimensionality. In the following section, We take advantage of the balancing properties of propensity score methods to measure the treatment effect of the CRS.

4.3 Propensity Score Matching Algorithm

Based on work of Rosenbaum and Rubin (1983), an alternative approach to estimate the treatment effect between comparison groups is Propensity Score Matching (PSM). The following

[3] With increasing number of variables (X_n), it is difficult to find exact matches for each of the treated units.

description of PSM draws heavily from a wide variety of previous works which focus on binary treatment or programs. Motivated by evaluation of labor market program, Heckman, Ichimura and Todd (1998), Dehejia and Wahba (2002), and Smith & Todd (2005) use PSM to estimate the impact of training programs on employees' income. Meanwhile, a rich literature exists in formulation the approach to the analysis of causal effects in observational studies. Galiani, Gertler and Schargrodsky (2005) study the effect of water supply on child mortality. Trujillo, Portillo and Vernon (2005) analyze the impact of health insurance on medical-care participation. Lavy (2002) estimates the effect of teachers' performance incentives on pupil achievement. The general story behind their approaches is straightforward. In experimental design, the two treatment groups can be compared, because the two treatments are drawn from the same population. In the observational experience, however, it cannot assume that the populations between two treatments are derived from the same population. The PSM find a nontreated unit that is similar to a participating unit, allowing the estimation of the treatment's impact as the different between a participant and the matched comparison case. The result will provide an estimation of the mean impact for the participations.

The PSM is to compare cases that are similar in terms of x_n, where participating units are matched with untreated units based on an estimate of the probability (i.e. the propensity score) that the unit receives the treatment. The propensity score can be conveniently represented as a scalar value, which can then be used to balance observed differences between treatment and control group (balancing refers to the fact that the distribution of the observable factors, X_n, should not differ across the treatment and control group after conditional on the propensity score). By using the PSM, we assume the adjusted pre-treatment differences allow us to draw the causal inferences as if the data set were random (Imbens and Wooldridge 2009).

4.3.1 Estimating the Propensity Score

Rosenbaum and Rubin (1983) define the propensity score is a balancing score for X_n, $b(x_n)$, which assure the conditional distribution of X will be the same for teated ($t = 1$) and control ($t = 0$) units by given value of $b(x_n)$. The propensity score estimation for an individual n ($n = 1,2, \dots, N$) occurs by estimating the probability of a treatment ($t_n = 1$), given the covariates, x_n. The standard probability model can be used for estimating the propensity score. Most applications take advantage of the logit model:

$$\hat{P}(X_n) = Pr(t_n = 1|X_n) = \frac{e^{g(X_n)}}{1 + e^{g(X_n)}},$$

where $g(X_n)$ is made up of linear, higher-orders, and interacted covariates so to obtain an ignorable treatment assignment (Dehejia and Wahba, 2002). The form of propensity score estimators can also utilizes the probit model:

$$\hat{P}(X_n) = Pr(t_n = 1|X_n) = \Phi[g(X_n)]$$

where the $\Phi(\cdot)$ denotes the standard cumulative normal distribution. Logit and Probit models casually provide similar estimation of propensity score.

4.3.2 Variable Selection in Parametric Propensity Score Estimation

In practice, the functional form of the propensity score model is unknown (Dehejia and Wahba 2002). Therefore, the primary specification issues driving the estimation of propensity score are to decide on the model to estimate the propensity scores and well-defined criteria for variable selection. As showed previous section, the linear logistic regression model can be used as the propensity score models. The interaction terms and higher order transformations are utilized to count for non-linear relationships.

The variable selection becomes an essential component in PSM. The choice of variables for propensity score model plays a role in the bias values of the estimation (Smith and Todd 2005). For each application, it is important to consider what factors make the comparison units distinct from treated units. Essentially, variables should be included based on the researchers' knowledge of the subjects. In their work, Heckman et al. (1998) provide the evidence that a rich set of relevant variables that are related to the program-participation decision results lowest estimate bias in PSM. Higher bias estimation is obtained for including a set of irrelevant variables. Also, a variable selection should account for nonlinear relationships in the model. In their study, Rubin and Thomas (1996) recommend that the relevant variables should be included from a theoretical bases and previous research that it is related to the outcome and the choice of treatment even if it is not statistically significant. In most practice, one selects the variables according to the data-driven ways. Most applications use stepwise variable section algorithms based on a predetermined level of balance. The balance can be tested by determining difference in mean across treated and comparison units are not significantly different from zero.

For parametric logistic regression model, I adopt the Dhejia and Wahba's (2002) algorithm for variable selection that is similar with Rosenbaum and Rubin's work (1984)[4]. The algorithm first start with a logit specification with main effect factors to estimate the propensity score. Then it stratifies the treated and comparison groups such that the estimated propensity scores within a stratum[5] are not significant different. Next, the algorithm conduct statistical test for the differences in means across treated and comparison units within each stratum. The balance is achieved if there is no statistically significant difference. If the covariates are not balanced, then one needs either divide the stratum into finer strata or adds interactions and (or)

[4] The algorithm of balancing test is so-called DW test, see Dehejia and Wahba (2002) for more detail.
[5] The stratum is one of equal propensity score range (i.e. 0-0.2, 0.2-0.4,…,0.8-1).

higher order polynomial terms into the model. The reevaluation will continue until the balance is achieved. The shortcoming of this algorithm is the balance may become difficult with the number of observable variables increasing. Besides the work by Dehejia and Wahba (2002), there are different balancing tests in the literature. In his work, Rosenbaum (2002) utilizes a variable trimming process. It recommends that the variables with the differences below a threshold significance level ($-1.5 > t > 1.5$) should be removed from the model. Smith and Todd (2005) test for the joint equality of covariate means across groups using the F-test. Here, we should note the treated and comparison groups will have little overlap if the participation model is perfectly predicted. The propensity score is not necessarily an efficient score if it does not create an adequate overlap within each stratum.

4.3.3 Matching Algorithm

After estimation of propensity score, there are a variety of ways to use propensity score to match compassion units with treated units. First of all, matching without replacement, meaning the each comparison group unit could be included as a matched case only once. Described by Dehejia and Wahba (2002), there are low-to-high, high-to-low, and random matching. Take the low-to-high for example, the treated units are ranked from lowest to highest propensity score. The lowest-ranked unit is matched first, and the matched comparison unit will not be used for further matching. The matching without replacement, however, increases bias when there is few comparison units with similar propensity score to the treated units.

Secondly, matching with replacement considers all comparison cases that are sufficiently close to a given treated case. The comparison units can be used more than once. If the number of comparison units is large, it may have number of good matches for each treated unit. By doing so, it can reduce variance in the treatment effect estimates. First, the *nearest-neighbor* matching will choose m individuals ($m \geq 1$) from comparison group as a match for treated individual with the closet propensity score. The untreated individual can be used more than once in the nearest-neighbor matching. With increasing m, it can reduce the variance due to utilizing multiple matches. However, it will increase bias since the matched propensity score are moving away from the 1st closet match.

Second, the *caliper* matching will use all of the units in the comparison group within a specified propensity score range (i.e. radius). In their work, Cochran and Rubin (1973) show that using calipers of width equal to 0.2 of the standard deviation of the propensity score can remove 98% of the bias of the estimation. Generally, the 0.25 standard deviations of the estimated propensity score can work well (Rosenbaum and Rubin 1985). Comparing with the nearest-neighbor matching, the advantage of the caliper matching is that it can use as many comparison units as available within a radius (Dehejia and Wahba 2002).

Third, the *kernel* matching compares the outcome of treated units to the kernel-weighted average over the units in the comparison group. The kernel estimation is a non-parametric estimation for the probability density function. Unlike the nearest-neighbor matching which gives zero weights for unmatched comparison units, the kernel matching will assign more weight to the comparison units with similar propensity score and less weight to the less similar units. Since it use more information, the kernel matching results the lower variance. A drawback of kernel matching is that it needs to choose the kernel function and the bandwidth[6] (smoothing) parameter. There are some different kernel functions. Since the different kernels impose nothing on the shape of the probability density function, choice of the kernel function is not a particular important (DiNardo and Tobias 2001). A trade-off exists in the choice of bandwidth. Increasing

[6] The bandwidth defines the neighborhood around the probability density function. The points falling in the bandwidth receive constant weight, while they receive zero weight when falling outside the bandwidth (Dinardo and Tobias 2001). High bandwidth values create a smoother estimated density function, which leads to a better fit.

the bandwidth will increase the bias but reduce the variance of the estimation by collecting more distant observation in constructing the counterfactual observation (Smith and Todd 2005).

Unfortunately, there appears to be uncertainty for how one should select matching algorithm. Generally, as the number of comparison unit rises, one decreases the variances of estimation with cost of increased bias (Dehejia and Wahba 2002). The different matching algorithms should yield similar results if there is substantial overlap in the comparison group and treatment group in terms of propensity score. To determine there is enough overlapping, the most straightforward method is to visual analysis of the density distribution of the propensity score in both treated and control groups. The overlaps should contains most subjects in both treated and control group's propensity score distribution. Heckman et al (1997) argue that the propensity score densities made at a points where the comparison group density is extremely small are likely to be inaccurate. They recommend adding the common support constraint to eliminate the subjects lying outside common region and within "trimming" level q. The same algorithm can also be found in Smith and Todd (2005).

Different matching methods are used in this section to ensure that similar counties are being compared. Such a comparison of the observable factors, X , relies on the previous literature in order to evaluate the appropriateness of comparison groups. X variables are as same as the variables that used in the third chapter (Participation in the Community Rating System of NFIP: An Empirical Analysis of North Carolina Counties) (see table 3.1). The means for the sample characteristics of entire sample are described in the table 4.1. The means for sample characteristics before matching and after matching for different parametric matching strategies are shown in the table 4.2. The first column lists the characteristics for the CRS county (treatment) group while the second column displays the characteristics for the non-CRS county (control) group. The t-test results (chi-square test for the dummy variable CAMA) clearly show statistically significant different distribution of the observable characteristics between the treatment and control group. Of 16 variables, CRS counties are significantly different from the non-CRS counties (expect the previous one year number of flooding, *Lag_1_floods*). 204 treated units will be matched with 996 control units. It implies that some control units will be given considerable weight.

The table 4.3 presents the results from four logistic regression models to estimate the propensity score. We first run the base logistic model which only includes 16 variables. The balancing test will then split the observations into different groups (i.e. strata) based on equally space intervals of the estimated propensity score. It then performs the t-test for the differences in each covariate mean within each stratum at 5% significant level (Dehejia and Wahba 2002). Table 4.2 shows that the means between treatment and control groups are statistically significant different before matching (expect the *variable Lag_1_floods*). Using Rosenbaum's variable inclusion threshold, where t-statistic must be greater than 1.50 (less than -1.50), we reduce the dataset: modified from the base logistic model, the Logistic 1 is created by dropping the variable of *Lag_1_floods*. In order to create to sufficient overlaps between treated and control groups, in Logistic 2, we add some higher ordered polynomial and interaction terms of the covariates that show significance after matching. We put *Lag_1_floods* back into the Logistic 3. The guideline for formulating the Logistic 3 regression models is to ensure the covariate to account for a legacy of flooding events that could have motivated mitigation activities over different time periods. We attempted over 100 different specifications of propensity score. With large number of covariate, it is difficult to pass the Dehejia and Wahba balancing test. Logistic 2 and 3 are the best function forms so far to achieve the balance within each stratum.

There are three matching algorithms for Logistic 1-3. Within each set of schemes using the same logistic regression, the first scheme uses *nearest-neighbor* matching (1-on-1). The second scheme uses the *caliper* matching by setting propensity score range of width equal to 0.2 of the standard deviation of the estimated propensity score. The third scheme uses nonparametric normal *kernel* matching. Generally, the table (last page) shows the different matching algorithms has resulted in balanced covariate between the treatment and control groups. Within Logistic 1-3, it is clear that much less imbalance occurs when we use kernel and caliper rather than nearest-neighbor. All schemes using nearest-neighbor 1-on-1 matching could not remove most significant difference between two groups. The use of many-on-more (from 2 to 5) did not help either. Although many variables are marginally better matched in Logistic 1, little significant improvement can be discerned when we use caliper methods in Logistic 1. Nine out of 15 variables are still significantly different between the treated and control groups in Logistic 1 (Caliper). In contrast, Logistic 2 and 3 show the caliper algorithm's remarkable ability of randomization to help attain balance in covariates, though three covariates in Logistic 2 and two covariates in Logistic 3 are remain imbalance. We set up the caliper with 0.25 of the standard error in practice. The results showed the reduction in the number of balancing covariates.

Among nine matching schemes, Logistic 2 Kernel and Logistic 3 Kernel are only two matching methods that have generally resulted in balanced covariate distributions between treated and control groups. The significant differences picked up by the t-test are for *College* and *CAMA* in Logistic 2 Kernel. *College* and *Average_tax* are significant difference in Logistic 3 Kernel. Our practice test shows much more imbalances occur when we drop each (or both) variables. We set up bandwidth in 0.06 as the STATA package default value. One wants to choose the bandwidth as small as the data allows. However, there is always a trade-off between the bias of the estimator and its variance. With less than 0.06 bandwidth, the result from kernel matching generally increases the degree of imbalance in difference between treated and control groups.

4.4 Non-Parametric Propensity Score Estimation: An Application of Boosting

In our application, the propensity scores are unknown and so as the correct functional form for the propensity score model which account for all covariates related to both CRS participation and property damage prevention. As originally proposed by Rosenbaum and Rubin (1984), Dhejia and Wahba (2002) use parametric models with selected interaction and higher ordered polynomial terms for estimating the propensity score. However, with more selected variables adding into the model, it becomes more and more difficult to achieve the balance within each stratum. McCaffrey, Ridgeway and Morral (2004) suggest that the boosting method may create better balance in covariates by using flexible non-parametric modeling. In addition to the parametric models for estimating propensity scores, we utilize a more flexible, nonparametric application via the generalized boosted model (GBM). Boosting allows models to be specified with large numbers of covariates in a nonlinear fashion. Our preliminary result shows that the GBM does not appear to be any benefit to create the balance. This issue will be further investigated in following section.

The description of boosting, GBM, and its connection to the PSM in this section relies heavily on the work by McCaffrey, Ridgeway, and Morral (2004). The boosting method can combine the number of simple functions which, individually, is poor approximation to the function of interest. In contrast, the combination of the simple functions can approximate a smooth function that uses a large number of covariates to fit the nonlinear surface and predict treatment assignment (Freund and Schapire 1999). As the boosting procedure, GBM uses regression trees as the sample functions to smooth the function of interest. The regression tree is a nonparametric method which uses the recursive algorithm to estimate a functional relationship by partitioning a data space and representing each partition by the sample mean of that space (Breiman et al 1984). Take our application for example, a basic partition of dataset may occur by splitting individual counties by the number of flood events which is less than or equal to one in the last year and those counties have flood events more than one time (The split can start between any pair of observed values of any of covariates). Next, the partition will be then subdivided into four distinct groups (i.e. flood events<=0 and CAMA county, flood events>=0 and CAMA county, flood events<=0, non-CAMA county, flood events>=0 and non-CAMA county).Within each division, the estimated function equals the sample mean of the outcome for observations within the partition. With continued split, it adds additional interaction between the variables and complexity of the tree. The algorithm chooses splits by minimizing prediction error. The GBM linearly combines all single trees to estimate a smooth function of large number of covariates.

To describe the boosting algorithm in GBM, we take a logistic transformation of propensity score $p(x)$ which ensures the estimation will always be in [0, 1]:

$$p(x) = \frac{1}{1 + \exp\left(-g(x)\right)} \qquad (2)$$

Where $g(x)$ represent some unknown function form of x. To estimate $p(x)$, we utilize the expected Bernoulli log-likelihood function:

$$E\big(LL(p)\big) = E(t\big(logp(x) + (1-t)\log\big(1-p(x)\big)\,\big|x\big) \qquad (3)$$

We use equation (3) substitute $p(x)$ in equation (3). The equation (3) then becomes the likelihood function of $g(x)$:

$$E\big(LL(g)\big) = E(t\big(g(x) - \log\big(1-\exp\big(g(x)\big)\big)\,\big|x\big) \qquad (4)$$

Instead of assuming $g(x)$ to be a linear combination, boosting algorithm allows $g(x)$ to be a flexible function form. The algorithm then maximizes the equation (4) to find the function $g(x)$.

Rather than modeling propensity score directly, GBM algorithm starts by setting the log-odds of treatment assignment to a constant value, $\hat{g}(x) = \log\left(\frac{\bar{t}}{1-\bar{t}}\right)$, where $\bar{t}$ is the proportion of treated of observation. The algorithm then makes the improvement to fit the model with iterations by adding a small adjustment, $h(x)$. The goal is to find the $h(x)$ that can increase the expected log-likelihood:

$$E(LL(\hat{g}(x) + \lambda h(x)) > E(LL(\hat{g}(x))$$

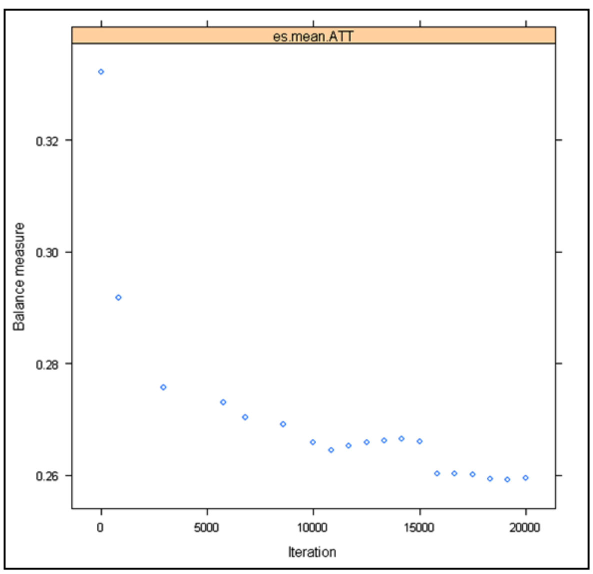
where $\hat{g}(x) \leftarrow \hat{g}(x) + \lambda h(x)$, λ represents some step size. $\lambda h(x)$ represents an improvement in the log odds from previous iteration. In order to find the right $h(x)$, Friedman (2001) suggest to derivative of (4) respect to $g(x)$:

$$h(x) = \frac{\partial E\big(LL(g)\big)}{\partial g(x)} = E\left(t - \frac{1}{1 + \exp\left(-g(x)\right)} \mid x\right) = E(t - p(x)|x)$$

Therefore, the adjustment, $h(x)$, is a type of residual of the expected log-likelihood, which is the different between the treatment indicator, t , and the probability of assignment to the treatment, $p(x)$. The regression tree estimates the residual, $(t - p(x))$, using a flexible iterative least squares procedure. The tree first splits the observations into different regions. The residuals are homogeneous within each region. The tree then estimates the optimal adjustment of $\hat{g}(x)$, $h(x)$, conditional on x in the same region. The algorithm then uses a line search to find the coefficient λ with the greatest increase in the log likelihood. λ is called the shrinkage value. The shrinkage means reducing the impact of each additional tree to avoid overfitting (Schonlau 2005).

The GBM requires no functional form for estimating the propensity score. However, the most boosting algorithm requires the specification of at least three parameters before the estimation (Friedman 2001). First is the number of iterations (i.e. number of splits for the trees) to minimizing prediction error. Second is the number of the variable interactions allowed. Third is the shrinkage coefficient. The smaller shrinkage value can reduce the impact of each additional split of trees to avoid overfitting the data. The GBM catalogs a set of propensity scores for each iteration. After running all the iteration, an optimal set of propensity scores are chosen. We fit the GBM using the generalized boosted modeling package developed at the RAND Corporation (McCaffrey, Ridgeway and Morral 2004). For example, by using all the variables from the table 1, the figure 1 describes the boosting procedure uses 18960 iterations to find the best maximum likelihood estimation of equation (4).

Figure 4.1: This graph depict the relationship between the average effect size and the number of iterations for the basic estimation of propensity scores. The optimal point is found after 18960.



The table 4.4 shows the results from four different nonparametric propensity score matching using general boosting model (GBM). The first two models (boost 1 and boost 2) include all variables within the dataset and only vary in the size of shrinkage coefficient. Similar with boost 1 and boost 2, the second two models (boost 3 and boost 4) use same set of shrinkages (0.01and 0.005), but dropped the variable, *Lag_1_floods,* which has t-test less that is less than 1.50 (t-test of *Lag_1_floods* = 0.4). We use these different algorithm settings to test the sensitivity of our estimation.

Compared to the balance in mean difference of covariates before GBM score matching, the table3 shows the matching leads to better balance. However, compared with the results from parametric models, relatively more unbalances are found. Boost 1 has 8 out of 16 covariates unbalanced. Using a smaller shrinkage value (0.005), 6 covariates were still unbalanced in Boost2. For the matching results in models without *Lag_1_floods,* similar results are found when checking the Boost 3 and Boost 4. 7 covariates remind unbalanced after matching. Whereas the some studies have shown that boosting outperforms logistic regression when it comes to prediction (Bauer and Kohavi 1999, Friedman 2001). All four models using GBM could not remove all significant difference between treated and non-treated groups. Our application confirms that good predictive ability may not result balancing matching (Rubin 2004). It suggests that there does not appear to be any benefit in using GBM for treatment effect estimation in our application. Our estimation for CRS impact on property damage reduction will base on logistic model estimated propensity score.

4.5 Estimates the Effect of CRS on Property Damage Reduction

In cross sectional estimation, after propensity scores have been estimated, the impact of the CRS creditable activities is calculated by an estimation of the average treatment effects for the treated group:

$$ATT = \frac{1}{N_1}\sum_i \left[Y_{1i} - \sum_i W(i,j)Y_{0j}\right],$$

where N_1 is the number of treated units, Y_{1i} is the outcome (i.e. property damage in flood events) for treated unit i, Y_{0i} is the outcome for control unit j, and weight $W(i,j)$ depends on the distance between the estimated propensity score between unit i and j. Different matching methods will use different weighting functions (Smith and Todd 2005).

In casual effect estimation, it is also reasonable to calculate the Average Treatment Effect (ATE):

$$ATE = \frac{1}{N}\sum_i \left[Y_{1i} - \sum_i W(i,j)Y_{0j}\right],$$

where N is the number of all units. First, we need to know the treatment effect on the groups where the treatment actually applied (ATT). Second, we can also estimate what might have happened if the treatment is applied on both groups (ATE). In this paper, we focus on ATT as the quantity of interest when it is conceptually or algebraically simpler.

The estimation of standard errors of propensity score matching is obtained using bootstrap methods. It is difficult to calculate the standard errors for the treatment effect in PSM by using conventional methods. Because the estimation should also include the variance due to the propensity score estimation, common support imputation, and the treated individuals matching. Lechner (2002) suggests using bootstrapping as an alternative to asymptotic approximations for obtaining standard errors, confidence intervals, and P-values for test statistics. Based on bootstrapping method, re-estimation a new sample of the same size will be drawn with replacement and all the steps including from first steps (i.e. propensity score, common support, etc.). The repeating bootstrapping will lead to the distribution of the means and standard error for the estimated average treatment effects is treated as the population mean and standard error.

The table 4.5 presents the estimates of ATT from different parametric matching models. As the statistics show, the impacts by treatment (CRS participation) are different in term of propensity damage changing cross all matching schemes. While result of Logistic (1on1 and caliper) has different sign which may caused by large number of imbalance covariates, all matching schemes in Logistic 2 and 3 show the property reduction in the same direction, that is, the CRS counties has less property damage than non-CRS counties. Taking the result in Logistic 3 Kernel for example, average property damage for CRS counties is $14,837 lower than that for the non-CRS counties.

4.6 Difference-in-Differences Matching Estimates in Panel Data Structure

We should note that our study formulates the propensity score by using CRS participation across all 100 North Carolina counties from 1991 to 2005. The previous chapter has demonstrated the unobserved factor, accounts for cross-sectional, time invariant factors that influence the counties propensity to conduct flood hazard mitigation activities, exists in the analysis. For example, local government structure and perceptions of flood hazard, as well as idiosyncratic features like history or culture, which are unobserved or unobservable, may affect CRS participation. The cross-sectional matching assumes that the mean of outcome are independent from the treatment assignment after conditioned on the observable factors. As such, it does not account for unobservable factor that may affect local hazard mitigation decisions. The selection bias may be also caused by some unobservable characteristics instead of only resulting from the differences in observable factors in treated and control groups (Rubin 1997, Heckman, Lalonde and Smith 1999). Therefore, the cross-section approach is problematic in our application, because some systematic differences between the treated and control groups may exist even after conditioning on observables.

Heckman et al (1997) employed panel data and Difference-in-Difference (DID) method to calculate the treatment effect. The DID matching strategy allows for the unobserved heterogeneity in outcomes between the treated and control groups (Smith and Todd 2005). We start with a simplest example to describe the DID estimation. The property damage due to flooding are observed for two groups of counties for two time periods. First group of counties participates into CRS in the second period of time but not in the first period. The second group of counties doesn't participate into CRS in both periods of time. DID method subtracts the average property damage changing between two time periods in the second group (non-CRS group) from the average property damage changing between two time periods in the first group (CRS group). As the result, DID method removes the time-invariant unobservable effect that may not captured by propensity score method. In their application, Smith and Todd (2005) demonstrate that DID estimator perform better than the cross-sectional matching method in panel data structure.

In this section, we take advantage of our panel data structure. The DID propensity score matching estimator assume:

$$E(Y_{0t} - Y_{0t'} | P, T = 1) = E(Y_{0t} - Y_{0t'} | P, T = 0)$$

And the DID estimator can be written as:

$$DID = \frac{1}{N_1} \sum_{i} \left\{ (Y_{1it} - Y_{0it'}) - \sum_{i} W(i,j) \big(Y_{1jt} - Y_{0jt'}\big) \right\}$$

where, $W(\cdot)$ is estimated by the cross-sectional matching estimators which have been discussed before. t and t' are the time indicator for after and before the participation of the CRS. $(Y_{1it} - Y_{0it'})$ is the difference in outcome for treated unite after and before participation. This difference is then further differenced with respect to the after and before difference of the matched control groups, $\left(Y_{1jt} - Y_{0jt'}\right)$. DID matching is similar with fixed-effects and can eliminate the unobservable individual specific effect.

In the table 4.6, the Kernel Matching of Logistic 2 and Logistic 3 are the best two models generally meet the assumption about ignorable treatment assignment (except the variable of *College*). The results of using Logistic 2 (Kernel) and Logistic 3 (Kernel) with DID estimation are shown in Table (below). We first set bandwidth equal to 0.06 without trimming, which is the default value in STATA software package. In this case we find $27,106 property damage reduction in CRS counties. Similarly, we find estimated $28,991.95 reduction in Logitic 3 Kernel. However, both estimations are not statistically significant. We use different bandwidth and trimming value to test sensitivity of our estimation. Our results are mixed. Both models are quite sensible. The estimated average property damage reductions for CRS are not statistically significant in case of the trimming=0.02 with different bandwidths (0.06 and 0.1). Heckman et al (1997) recommend adding the common support constraint to eliminate the subjects lying outside common region. The figure 4.2 shows the estimation lacks of enough overlapping in the strata which is greater than 0.8 in estimated propensity score, may explain the inconsistent results. We increase the common support constraint by rising trimming level to 0.1. Given the consistent results from both Logistic 2 and 3, we estimate stable and statistically significant property damage reduction effects for CRS. Moving from cross-sectional matching estimation to DID of panel data estimation, the effect of CRS on propensity damage reduction increases from the range of approximated 14,837-17,537 to the range of 22,543-23,403. Since we prefer DID estimation which allows unobserved heterogeneity, our estimation provide some evidence that the cross-sectional estimation underestimates the property damage reduction effect from CRS mitigation projects.

4.7 Conclusions

The objective of the Community Rating System (CRS) is to encourage local communities to take additional efforts to mitigate flood risk (over the minimum NFIP requirements) and to initiate new flood protection activities. Little empirical evidence exists, however, to shed light on the impact of the CRS on flood related property damage reduction. In essence, estimating a treatment effect in an observational study is challenging. This chapter uses propensity score matching (PSM), an innovative analytic method, with empirical data from 100 North Carolina counties to assess whether the CRS actually results in lower property damage. PSM aims to balance the differences in observable county characteristics between CRS and non-CRS participants (when treatment assignment is non-ignorable) and (under certain conditions) allows one to draw causal inferences as if group assignment were randomized.

Evidence of the effectiveness of CRS has been provided in a study by Brody, et al. (2007), which indicates that flood damage can be decreased by approximately 15% by increasing CRS rating by 1unit. However, due to the endogenous nature of CRS mitigation activities, traditional regression models may prove inadequate and misleading. Instead, we apply the PSM method to correct sample selection bias due to observable differences between the CRS participants and comparison groups across all 100 counties in North Carolina from 1995 to 2010. After controlling for potential endogeneity, we estimate the effect of CRS on property damage reduction to be in the range of $14,837 to $23,403 per county, flooding event. This result coupled with Brody, et al (2007) suggests that CRS creditable mitigation projects appear to limit flood related property damage. Still, the magnitude of the reduced damage appears modest;

more research is needed to explore the robustness of these findings, and perhaps more importantly, the effectiveness of different CRS mitigation activities.

Our study shows the potential for applying PSM in the evaluation of causal effects of hazard mitigation projects on property damage reduction. The selection of covariates for the first-stage probability model has impact on PSM estimation. The results indicate that elimination of one variable (*Lag_1_flood*) resulted in a better model fit. Although there is substantial variation in the results, the findings show that all of the effects are in the same direction, indicating that CRS effectively reduces (albeit somewhat modestly) the average property damage during a flood event. However, we expect the matching of CRS and non-CRS counties for comparison may be problematic due to a lack of balance in constructing the counterfactual and because of the possible influence of unobservable factors. For the DID exercise, we find evidence that time-invariant unobservable effects do influence selection, which may cause downward bias the estimation of treatment effects. From our preferred DID, the effect of CRS on propensity damage reduction is in the range of $22,543 to $23,403 per county, per flood event. While somewhat modest, these estimates of damage reduction would increase by two orders of magnitude when scaled up to the state level. CRS may also have impacts of flood-related fatalities (which we do not analyze due to very sparse data).

The *CRS Coordinator's Manual* contains an easy-to-use checklist that allows local officials to determine if their community currently undertakes enough activities to attain Class 9 (>499 CRS points), and many recommended activities can be implemented for a relatively low up-front cost (e.g. public information activities Series 300-responding to inquires to identify a property's FIRM zone can earned up to 138 CRS points) (FEMA 2007, page 120-3). Any mix of flood hazard mitigation activities from credible CRS activities that results in 500 points is sufficient to attain a score of 9, and additional activities can lower the score. Therefore, with low cost of CRS participation, combining with the insurance premiums discount, the benefit of CRS from the reduction of property damage could be attractive to the local community. The effectiveness of the various CRS activities, however, remains an important topic for future research. For example, it may be the case that cheaper and easier mitigation activities are less effective at actually mitigating flood damage. Moreover, since our models only account for CRS adoption (extensive margin) and we do not analyze the level of mitigation (reflected in total CRS points – the intensive margin), our estimates can be viewed as conservative.

Despite the inconsistent estimation with small trimming level (less than 0.1), other results are consistent across different models and show the CRS can effectively reduce the property damage at the county level. As such, our results provide some insight into the development of future evaluation strategies aimed at addressing the effectiveness in mitigation planning, but we acknowledge that our propensity score estimation results are lacking in terms of balance and overlap – important metrics for evaluating the efficacy of the PSM approach. Keeping these limitations in mind, we recommend that future studies explore different methods for covariate selection in the first-stage probability model. Increasing our sample size to the multi-state level may result in more balanced estimation of PSM and increase the accuracy in expected relationships between treatment and outcomes. Our method provides researchers with a potential strategy to evaluate the performance of similar public policies.

Table 4.1: Data Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
CRS_dummy	0.170	0.376	0	1
PreCRS_floods	1.940	1.038	1	6
floods	0.297	0.573	0	4
Lag_1_floods	0.353	0.629	0	5
Precipitation	47.551	6.041	37.266	71.607
Water_percentage	5.225	12.325	0	69.280
CAMA	0.200	0.400	0	1
Avg_Tax	0.352	0.120	0.126	0.892
Student_Teacher	14.431	1.182	8.756	20.278
Crime_density	0.102	0.057	0	0.376
Hu_density	77.196	103.171	4.806	751.182
Income	40.468	8.297	22.499	68.248
Senior	14.514	3.492	5.562	26.262
College	14.944	7.522	6.770	51.989
CRS_muni	8.821	20.717	0	100
CRS_neighbor	14.644	16.212	0	75
NFIP_year	9.738	6.116	0	29

Table 4.2: Sample Means before and after Parametric Estimation of Propensity Score Matching.

	Before Match		**Logistic 1**	**Logistic 1**	**Logistic 1**
	Mean	Mean	1 on 1	Kernel	Caliper (0.012)
Variable	Treated	Control	Control	Control	Control
PreCRS_floods	2.6552	1.7893***	2.6618*	2.3371	2.4333
		(12.91)	(1.72)	(0.32)	(0.57)
floods	0.42529	0.3745**	0.40196	0.23861**	0.22778***
		(2.05)	(3.65)	(2.09)	(3.19)
Lag_1_floods	0.39847	0.37934	-	-	-
		(0.4)			
Precipitation	50.215	46.99***	50.347***	51.064*	52.127***
		(8.9)	(-3.62)	(-1.73)	(-2.95)
Water_percentage	16.009	2.9537***	16.15***	4.2257***	3.2731***
		(16.98)	(7.81)	(3.22)	(5.11)
CAMA	0.31801	0.16303***	0.31863***	0.15552***	0.11667***
		(5.86)	(5.52)	(2.74)	(4.27)
Avg_Tax	0.4745	0.3471***	0.45752***	0.37474***	0.38477***
		(15.58)	(5.02)	(3.01)	(3.93)
Student_Teacher	13.985	14.374***	14.199***	13.86	13.601***
		(-3.76)	(-3.24)	(1.57)	(3.77)
Crime_density	0.13032	0.09271***	0.13462***	0.14958**	0.16166***
		(10.05)	(-5.52)	(-2.55)	(-4.51)
House_density	206.06	53.625***	199.07	164.48	189.29
		(24.27)	(-0.14)	(0.97)	(1.06)
Income	44.64	40.481***	43.351	42.486	43.092
		(7.44)	(0.71)	(1.04)	(0.78)
Senior	12.779	14.962***	12.852	13.203	12.893
		(-9.34)	(-2.4)	(-0.66)	(-0.58)
College	21.878	14.024***	12.583	20.123	20.845
		(16.21)	(0.23)	(0.24)	(0.54)
CRS_Muni	33.112	3.9783***	11.287***	15.717	12.792***
		(23.88)	(7.3)	(1.85)	(4.62)
CRS_neighbor	24.76	13.366***	9.5728	14.239***	10.849***
		(10.4)	(8.21)	(3.56)	(5.64)
NFIP_year	15.475	10.211***	13.961**	13.687	14.533
		(11.96)	(2.01)	(0.43)	(1.62)
N (Untreated)	996	-	269	269	269
N(Treated)	-	204	67	66	63

Note: T-statistics of the difference in means between the treatment and control groups are in parentheses (Chi-sq for dummy variable). * statistically significant at the 10 percent level, ** statistically significant at the 5 percent level; *** statistically significant at the 1 per cent level.

Table 4.2 (continued): Sample Means before and after Parametric Estimation of Propensity Score Matching.

Variable	**Logistic 2** 1 on 1 Control	**Logistic 2** Caliper (0.014) Control	**Logistic 2** Kernel Control	**Logistic 3** 1 on 1 Control	**Logistic 3** Caliper (0.029) Control	**Logistic 3** Kernel Control
PreCRS_floods	3.299	2.3889	2.2506	2.7895	2.4286	2.1858
	(-1.51)	(0.74)	(0.88)	(-0.92)	(1.53)	(0.92)
floods	0.28431	0.33909	0.1277	0.1358**	0.175	0.13026
	(1.07)	(1.3)	(0.97)	(1.98)	(0.38)	(0.71)
Lag_1_floods	-	-	-	0.26173	0.575	0.23662
				(0.58)	(-0.89)	(0.64)
Precipitation	47.061*	45.07	45.617	45.75	45.653	48.39
	(1.74)	(1.14)	(0.7)	(1.01)	(1.15)	(-0.04)
Water_percentage	5.4828	2.915**	6.9466	1.4828	0.13125	0.4383
	(1.67)	(2.2)	(0.64)	(0.67)	(1.49)	(1.34)
CAMA	0.16049	0.11111	0.25804***	0.16049	0.1625	0.1625
	(1.56)	(1.52)	(2.63)	(1.56)	(1.53)	(1.53)
Avg_Tax	0.5070	0.43557	0.41604	0.41002	0.37315	0.38935**
	(-1.07)	(1.29)	(0.52)	(0.94)	(-0.95)	(1.97)
Student_Teacher	15.453	14.41	14.072	14.608	16.036	15.612
	(-1.41)	(-1.04)	(-0.88)	(-0.095)	(-1.74)	(-1.01)
Crime_density	0.0618***	0.11454	0.11041	0.13344	0.13471	0.11567
	(12.04)	(0.71)	(0.4)	(-0.24)	(-0.86)	(0.2)
House_density	84.984***	214.16	127.62	249.06	177.18	172.63
	(7.18)	(0.07)	(0.66)	(-1.16)	(1.78)	(1.82)
Income	41.731	44.752	50.124	44.752	47.208	48.095
	(0.61)	(-1.48)	(-0.82)	(1.48)	(-1.08)	(-1.35)
Senior	12.049	10.179**	13.353	14.684*	8.3783*	11.458
	(0.07)	(2.12)	(0.21)	(-1.78)	(1.98)	(0.77)
College	16.961***	29.917*	23.193*	10.389***	28.586***	29.523**
	(3.86)	(-1.6)	(-1.77)	(5.59)	(-1.84)	(-2.18)
CRS_Muni	28.571	16.162	29.207	11.111***	15.1948	8.1133
	(0.34)	(1.21)	(0.2)	(3.06)	(0.17)	(1.63)
CRS_neighbor	26.832	35.926	23.402	18.772	22.381	16.509
	(-1.48)	(-1.26)	(-0.24)	(1.14)	(0.05)	(0.81)
NFIP_year	20	17.556	16.764	17.368*	14.571	15.164
	(-0.99)	(-0.69)	(-0.14)	(-1.98)	(0.8)	(-0.98)
N (Untreated)	352	352	352	414	414	414
N(Treated)	80	89	88	163	136	217

Note: T-statistics of the difference in means between the treatment and control groups are in parentheses (Chi-sq for dummy variable). * statistically significant at the 10 percent level, ** statistically significant at the 5 percent level; *** statistically significant at the 1 per cent level.

Table 4.3: Parametric Propensity Score Estimation by logistic functions.

Variables	Base Logistic	Logistic 1	Logistic 2	Logistic 3
PreCRS_floods	0.2865*** (0.0172)	0.0017 (0.0290)	0.015 (1.3467)	0.3241*** (0.1098)
floods	0.2381 (0.2242)	0.2171*** (0.0817)	0.1475 (0.2778)	0.1917 (0.2773)
Lag_1_floods	-0.1452 (0.2147)	–	–	-0.3045 (0.2601)
Precipitaion	0.1967*** (0.0277)	0.1986*** (0.0546)	0.2422*** (0.0635)	0.2265*** (0.0383)
Water_percentage	0.1821*** (0.0227)	0.3516*** (0.1368)	0.4805*** (0.1103)	0.4290*** (0.1330)
CAMA	-4.6479*** (0.9834)	-2.2586 (2.2990)	-2.7109** (1.2643)	-2.4229 (1.7584)
Avg_Tax	4.1725 (3.0493)	6.1228*** (1.1384)	8.9536** (4.4768)	7.6284* (4.4257)
Student_Teacher	-0.4976** (0.2024)	-0.65** (0.2646)	-0.7692** (0.2867)	-0.7830*** (0.2826)
Crime_density	6.2496** (2.2233)	6.5307** (2.8214)	8.1586** (3.3727)	7.9426** (3.1071)
House_density	0.0179*** (0.0023)	0.0223 (0.0032)	0.0248*** (0.0033)	0.0233*** (0.0034)
Income	0.0029 (0.0306)	0.0264 (0.0408)	0.0115 (0.0428)	0.0186 (0.0381)
Senior	-0.3552*** (0.0951)	-0.3546*** (0.1243)	-0.3391*** (0.1098)	-0.3628*** (0.1161)
College	-0.0176 (0.0279)	-0.0227 (0.0369)	-0.0125 (0.0376)	-0.0149 (0.0408)
CRS_Muni	0.0741*** (0.0133)	0.1014*** (0.0220)	0.1001*** (0.0203)	0.0996*** (0.0214)
CRS_neighbor	0.0375*** (0.0090)	0.0163 (0.0110)	0.2247*** (0.0624)	0.0927** (0.0393)
NFIP_year	0.0536* (0.0287)	0.1425*** (0.0333)	0.1693*** (0.0404)	0.1635*** (0.0363)
PreCRS_flood*Precipitation	–	–	-0.0068 (0.0270)	–
Water_percentage^2	–	–	0.0065 (0.0032)	0.0052 (0.0114)
Water_percentage^3	–	–	–	0.00002 (0.00013)
CAMA*Water_percentage	–	–	-0.6033** (0.1699)	-0.5815** (0.2758)
Avg_Tax^2	–	–	0.2716 (0.2240)	0.4621 (0.5301)
Student_Teacher^2	–	–	0.0325 (0.0834)	–
Student_Teacher*Crime_density	–	–	–	-0.00367 (0.0043)
CRS_neighbor^2	–	–	-0.0083*** (0.0022)	-0.0017** (0.0008)
CRS_neighbor^3	–	–	0.00008*** (0.00002)	–
Constant	-0.6416 (2.6396)	2.2154 (3.6170)	2.1790 (3.2950)	3.1765 (3.3507)

Table 4.3 (continue): Parametric Propensity Score Estimation by logistic functions.

	Base Logistic	Logistic 1	Logistic 2	Logistic 3
Log likelihood	-257.409	-257.443	-235.024	-241.070
Pseudo R2	0.6271	0.6271	0.6596	0.6508
LR chi-square(16, 15,23,22)	865.93	865.87	910.7	898.61
P-value of LR	0.000	0.000	0.000	0.000
N	1485	1485	1485	1485

Note: standard errors in parentheses. * means that the estimation is significant at 10%; ** means that the estimation is significant at 5%; *** means that the estimation is significant at 1%. Pseudo R-square is used to show the explanation power of the model. The pseudo R-squared ranges from 0 to 1 with higher values indicating better fit. Likelihood Ratio (LR) tests the joint significance of all coefficients. LRs are distributed chi-squared with degrees of freedom equal to the number of variables added to the model

Table 4.4: Sample Means before and after General Boosting Model Score Matching

Variable	Before Match		Boost 1	Boost 2	Boost 3	Boost 4
	Mean Treated	Mean Control	shrinkage=0.01 Control	shrinkage=0.005 Control	shrinkage=0.01 Control	shrinkage=0.005 Control
PreCRS_floods	2.6552	1.7893*** (12.91)	2.04* (1.949)	2.08 (1.27)	2.041*** (3.69)	2.042** (2.607)
floods	0.42529	0.3745** (2.05)	0.373 (0.731)	0.311 (0.52)	0.305* (1.89)	0.307 (1.11)
Lag_1_floods	0.39847	0.37934 (0.4)	0.353 (0.674)	0.332 (1.046)	-	-
Precipitation	50.215	46.99*** (8.9)	47.806** (2.525)	48.452*** (3.188)	48.5*** (3.054)	48.552*** (2.933)
Water_percentage	16.009	2.9537*** (16.98)	4.393*** (6.474)	6.901** (2.528)	7.12** (2.235)	7.199 (1.38)
CAMA	0.31801	0.16303*** (5.86)	0.242 (1.572)	0.262 (0.876)	0.26 (0.859)	0.26 (0.841)
Avg_Tax	0.4745	0.3471*** (15.58)	0.369 (1.271)	0.401 (1.855)	0.301** (2.16)	0.352 (1.034)
Student_Teacher	13.985	14.374*** (-3.76)	14.399 (-1.84)	14.239 (-1.061)	14.203 (-0.862)	14.19 (-0.79)
Crime_density	0.13032	0.09271*** (10.05)	0.113*** (2.73)	0.117** (2.528)	0.127 (1.869)	0.101* (1.912)
House_density	206.06	53.625*** (24.27)	93.689*** (5.738)	88.03*** (6.442)	88.044** (2.098)	87.397** (2.123)
Income	44.64	40.481*** (7.44)	43.551 (1.159)	42.204* (1.781)	42.17* (1.66)	42.125* (1.708)
Senior	12.779	14.962*** (-9.34)	13.747** (-2.411)	14.15** (-2.436)	14.18 (-1.291)	14.223 (-0.953)
College	21.878	14.024*** (16.21)	17.671** (2.415)	17.983 (1.82)	18.009*** (2.642)	17.975*** (2.659)
CRS_Muni	33.112	3.9783*** (23.88)	8.977 (0.223)	10.314 (0.193)	10.002 (0.294)	9.91 (0.376)
CRS_neighbor	24.76	13.366*** (10.4)	18.989 (0.32)	18.643 (0.95)	18.724** (2.376)	18.767** (2.405)
NFIP_year	15.475	10.211*** (11.96)	12.52* (1.949)	11.652 (1.37)	11.552 (1.62)	11.519 (1.233)

Note: T-statistics of the difference in means between the treatment and control groups are in parentheses (Chi-sq for dummy variable). * statistically significant at the 10 percent level, ** statistically significant at the 5 percent level; *** statistically significant at the 1 per cent level.

Table 4.5: CRS Effect on Propensity Damage Reduction, Cross Sectional Propensity Score Matching

Unmatched Sample		**Treated**	**Control**	**Difference**	**S.E.**	**t**	**P-value**
		321,464	291,723	29,741	63279.12	0.47	0.643
Model	**Matching**	**Treated**	**Controls**	**Difference**	**S.E.**	**t**	**P-value**
Logistic 1	1 on 1	244,525	209,591	34,934	79780.23	0.44	0.664
Logistic 1	Caliper (0.063)	243,853	240,057	3,796	39282.77	0.1	0.920
Logistic 1	Kernel	281,818	282,584	-766	14244.51	-0.05	0.961
Logistic 2	1 on 1	293,625	308,700	-15,074	9385.86	-1.61	0.123
Logistic 2	Caliper (0.071)	233,147	245,684	-12,537	9702.96	-1.29	0.212
Logistic 2	**Kernel**	**244,525**	**259,648**	**-15,123**	**7070.89**	**-2.14**	**0.045**
Logistic 3	**1 on 1**	**294,525**	**312,062**	**-17,537**	**6407.02**	**-2.74**	**0.013**
Logistic 3	Caliper(0.061)	220,525	232,362	-11,837	9538.35	-1.24	0.229
Logistic 3	**Kernel**	**244,525**	**259,362**	**-14,837**	**8288.70**	**-1.79**	**0.089**

Note: Property Damage is in 2000 dollar.
Difference = Property Damage in CRS – Matched Property Damage in non CRS counties.
Standard Errors are calculated by bootstrapping method.

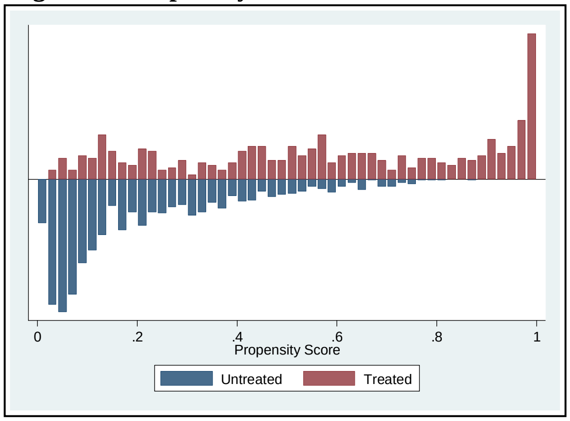
Table 4.6: CRS Effect on Propensity Damage Reduction, Difference-in-Difference Matching

	Logistic 2 (Kernel)				Logistic 3 (Kernel)			
	Property Damage Reduction	**S.E.**	**t**	**P-value**	**Property Damage Reduction**	**S.E.**	**t**	**P-value**
Bandwidth=0.06								
No Trimming	-27,106	18934.78	-1.43	0.1679	-28,919	23514.18	-1.23	0.232
Bandwidth=0.01								
Trimming (0.02)	-22,146	13927.64	-1.59	0.1275	-23,515	17950.68	-1.31	0.206
Trimming (0.1)	**-23,442**	**13471.29**	**-1.74**	**0.0972**	**-22,543**	**10689.27**	**-2.11**	**0.048**
Bandwidth=0.1								
Trimming (0.02)	-23,965	15974.36	-1.5	0.1492	-22,145	18002.31	-1.23	0.233
Trimming (0.1)	**-22,767**	**11499.5**	**-1.98**	**0.0613**	**-23,403**	**9174.874**	**-2.55**	**0.0191**

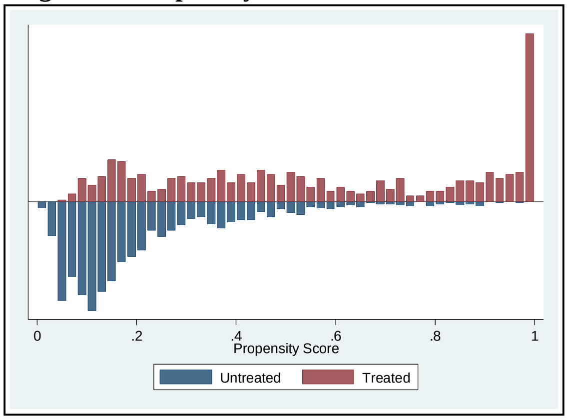
Note: Property Damage Reduction is in 2000 dollar.
Standard Errors are calculated by bootstrapping method.
STATA program default: Bandwidth=0.06, no trimming.

Figure4.2: This graph depicts the overlapping between the CRS and non CRS counties with similar propensity score.

Logistic 2: Propensity Score Estimation



Logistic 3: Propensity Score Estimation



Note: The treated group represents CRS counties; the untreated group represents non-CRS counties

Chapter 5: Estimation of a Dynamic Panel Data Model: Policy Learning in Hazard Mitigation

5.1 Introduction

Mandates for environmental management often originate at the highest levels of government. Commitment at the local level, however, can vary widely, and this ‘commitment conundrum’ can persist within top-down coercive arrangements as well as cooperative risk management agreements within the federal-state-local nexus. (Burby and May 1998). Under the authority delegated by federal and state governments, local governments are primarily responsible for zoning, planning, and managing hazard mitigation activities within their jurisdictions. The average tenure of local government officials and managers (typically 7-8 years) is generally adequate to allow for the interactive study of local policies and to monitor feedback from management practices. Therefore, local governments are able to adjust their mitigation policies and planning regulations to react to periodic natural hazard events such as floods, hurricanes, and earthquakes, and from changing environmental and socio-economic conditions. Brody, et al. (2009) describe this policy evolution in response natural disasters as a result of *policy learning*, a type of adaptive management approach. In adaptive management, the policies are designed as hypotheses, and policies are implemented as experiments to test those hypotheses (Holling 1995). Cumulative learning can occur with opportunity for trial-and-error studies (Lee 1993).

Following Brody, et al.(2009), we consider policy learning with application to flood hazard mitigation projects. It is important for local government to maintain stability and transparency in planning and policy-making processes, so that agents and institutions can form reasonable expectations upon which to make development and investment decisions. As a result, the establishment of a new framework of hazard mitigation presents a considerable challenge, involving a change of momentum which requires commissioner meetings, public hearings, and ordinance revisions, all of which are costly. Nonetheless, Weir and Skocpol (1985) argue that the goals and objectives that policy makers pursue are influenced by the "meaningful reaction to previous policies". Hall (1993) contends that policies respond more to the consequences of past policy than to current social and economic conditions. Therefore, we postulate that hazard mitigation policy learning can be described in terms of a dynamic mechanism which is characterized by the presence of a lagged dependent variable among the regressors.

Our dynamic model was first introduced by Balestra and Nerlove (1966) to estimate the demand of natural gas at the household level. They argue that gas consumption is closely related to the stock of gas appliances in existence and that to a large extent it is governed by such stocks. Therefore, the behavior of the consumer can be best described in terms of a dynamic mechanism. In time-series analysis, a lagged dependent variable is included in the model to account for behavioral persistence – "the past can affect the future, but not vice versa" (Wooldridge 2002). In the previous chapter, we applied panel data models to control for unobserved individual heterogeneity. The *dynamic panel model* allows for modeling both dynamics and individual-specific effects. It thus enables us to parse out whether local officials are learning from the planning experience to pursue better mitigation outcomes or whether unobserved differences across counties are more persistent in their influence on mitigation activities.

Gujarati (2002, chapter 17) concluded three main reasons for lagged phenomena and dynamic models in a production framework: (1) psychological reasons: with force of habit, people do not change their behavior immediately following a external shock (e.g. income increase or price decrease); (2) technological reasons: technology may be slow to adopt or difficult to implement; (3) institutional reasons: institutions may limit economic choices and speed of adjustment. Within the context of comprehensive planning, policy learning not only stems from the outcome of current mitigation project buffering the adverse impact from the flood events. It may be also derived from alteration of the policy goals and mutual debates over the core value of the policy (Brody 2003). As a result, we consider policy learning as consistent over short periods of time and dynamic in nature. The dynamic panel model specifies both lagged dependent variables and unobserved effects which enable us to test for a type of dynamics that frequently occurs in community hazard mitigation (i.e. find out if past community hazard mitigation policy directly affects current policy) and to see whether individual specific effects drive this policy change over time.

This chapter addresses the dynamic nature in flood hazard mitigation policy learning by examining the patterns in score of Community Rating System (CRS) under the National Flood Insurance Program (NFIP) across all 100 counties in North Carolina from 1995 to 2010 with controls of flood experience, hydrological risk factors, local capacity, and socioeconomic factors. CRS is designed to encourage local governments to do more to reduce flood losses, protect their residents, and improve flood insurance coverage. By earning points for activities that exceed NFIP standards, CRS communities obtain reductions in flood insurance premiums for their residents. While the CRS has been recognized as a successful and mature program within the NFIP, the Federal Emergency Management Agency (FEMA) is seeking to develop innovative ways to enhance its operations and outcomes (CRS strategic plan 2008-2013). The goal of this study is to provide an empirical verification of whether the dynamic mechanism exists in the (self) policy learning process within the CRS communities. The empirical evidence will provide advice about policy design and further information for those who seek a better understanding of the relationships between policy formation and outcomes. The following section examines the existing literature on policy learning. We utilize CRS program as an empirical target for investigating learning within the context of the hazard mitigation planning.

5.2 Literature of Adaptive Management and Policy Learning

The concept of policy learning has been well documented in the previous literature (Helco 1978, Sacks 1980, May 1992, Holling 1996, Brody 2003). A conventional theory of conflict-oriented assumes policy formulation and implementation are driven by conflicts[7] in a given governmental structure and changing socioeconomic environment (Sabatier 1987, Bennett and Howlett 1992). The notions of learning suggest a new approach to public policy-making with consideration of substantive policy information processing and feedback. It argues that government agents can modify their actions by learning from and interpreting their previous policy initiatives. The notion of learning from public policy has been conceptualized by a long list of literatures, including "political-learning" (Heclo 1974), "government learning" (Etheredge 1983), "policy-oriented learning" (Sabatier 1987), "lesson drawing" (Rose 1991), "social learning" (Hall 1993), and "instrumental learning" (May 1992). While previous scholars working in different fields utilize different terms to conceptualize "learning", all notions imply the policy makers or political community take lessons from the observation of policy experience and problems, which lead to change in public policy-making (Bennett and Howlett 1992).

Policy development can be best understood as a process of collective political learning. It leads to alterations in behavior reflected in changed social policies and new policy innovations. Therefore policy must be regarded as both an independent and dependent variable (Heclo1974). In his study, Sacks (1980) analyzes the pattern of public choice in social policy from a state-

[7] The policy change "will ultimately entail a set of judgments that is more political in tone, and the outcome will depend, not only on the arguments of competing factions, but on their positional advantages within a broader institutional framework, on the ancillary resources they can command in the relevant conflicts, and on exogenous factors affecting the power of one set of actors to impose its paradigm over others."(Hall 1993)

centric perspective[8]. His work support Heclo's conclusion that the interaction of pressure groups and government has far less influence on the outcomes of public policy. The formulation of policy objectives and the choice of strategies for influencing societal behavior could be better explained by a "statist" approach. Following Heclo (1974), Hall (1993) studies the nature of social learning aligning with the theory of state:

"Their central contention (for the theory of state) is that the state, broadly understood as the executive, legislative, and judicial apparatus of the nation, has an important impact of its own on the nature of public policy and considerable independence from organized social interests and the electoral coalitions that might otherwise be said to drive policy."

His work, however, shows that social learning can neither be described entirely by a learning process taking place inside the state itself, nor by social pressures. May (1992) defines policy learning as the policy instruments or designs which are preferred by the policy domain with formal evaluation and limited comparison. While, rather than systematic policy evolution, trail-and-error procedures create the basis for responding to public problems; the self-correction is far from automatic due to the complexity of the political reality and evaluation of policy performance. Therefore, the political process should be seen as susceptible to path dependence (Pierson 2000).

While previous literatures on policy learning are in agreement on the principle impacts of previous policy efforts on current goals and objectives that policy makers pursue, they have different descriptions of the learning process. As Heclo (1974) has noted, the policy actors, or

[8] The state-centric suggests the policy is made by public officials, which emphasizes the autonomy of the state from societal pressure (Hall 1993).

‘policy middlemen’, who are able to influence policy making learn about the substance and process of past government efforts. This conceptualization is, however, too general to be used in empirical studies (Bennett and Howllett 1992). By adapting elements of individual and organizational learning to policy studies, Etheredge and Short (1983) describe the learning process in government as reflecting the intelligence and sophistication of administrative officials, at both the senior and junior levels of public service, and how administrative capital evolves due to knowledge accumulation and value change – both of which can enhance the effectiveness of government actions. While some political and sociological variables, such as current active political conflicts, input from the news media, and methodological innovations from university research, may also influence the process, policy makers appear to predominanrly adjust goals and techniques of policy in response to past experience and new information (Hall 1993). Sabatier (1987) expands the agent of learning from “policy middlemen” (Heclo) and state officials (Etheredge) to a policy network. He argues that “policy-oriented learning” is a major determinant of policy change. Policy change due to learning is best seen as characterized by fluctuations in dominant beliefs, which are influenced by experience within a given policy area over time. With limited capacities and time, policymakers in cities, regional governments, and nations could draw lessons from how their counterparts elsewhere respond, and this may affect how they deal with their own problems.

In summary, the literature on “policy learning” suggests that policy makers have an opportunity to learn and improve policy so that future decisions can proceed from better base of understanding. The CRS score is a proxy of the quality of local flood hazard mitigation and planning. Since all CRS creditable activities are voluntarily, the change in CRS scores reflect how the local policy decision making groups learn from previous adopted floodplain regulation, which can be a way to measure the policy learning in flood hazard mitigation planning. The following section presents details on dynamic panel data model measuring policy learning by using CRS score as both an outcome variable and a casual variable for local flood mitigation planning

5.3 Methods

The estimation approach underlying the dynamic model described in this section is a consideration of CRS mitigation policy in a policy learning framework (i.e. the CRS mitigation is not only influenced by flood experience, hydrological risk, local capacity, and socioeconomic characteristics, but also closed related to the previous CRS mitigation efforts and outcomes). The purpose of this section is to discuss the specific approaches that are applicable for estimating a dynamic model with panel data. We start with a basic dynamic panel data model with unobserved heterogeneity:

$$y_{it} = \gamma y_{i,t-1} + x_{it}\beta + v_{it}, \quad (v_{it} = c_i + \lambda_t + u_{it},) \qquad (1)$$

where the subscript i denotes the ith county ($i = 1, \ldots, 100$) and t denotes the t th year ($t = 1, \ldots 16$). y_{it} denotes the population weighted CRS points for each county from 1995 to 2010 (see Appendix for details). x_{it} is a K x 1 vector of time-varying exogenous regressors, including the constant term; β is a K x 1 vector of parameters to be estimated; c_i is a time-constant unobserved effect for country i ($c_i \sim N(0, \sigma_c^2)$; $\lambda_t$is a time-period effect, that is assumed to be a fixed parameter (estimated as coefficients of time dummies for each year in the sample), and u_{it} is random disturbance term, $u_{it} \sim N(0, \sigma_u^2)$. Variables in x_{it} are assumed to be strictly exogenous conditional on the unobserved effect, but may be correlated with c_i. When the scale factor $\gamma \neq 0$ the current state y_{it} depends on last period's state $y_{i,t-1}$, after controlling for c_i and x_{it}. If $\gamma = 0$, it means $y_{i,t-1}$does not help to predict y_{it} after unobserved heterogeneity has been controlled along with x_{it}.

5.3.1 Ordinary Least Square (OLS)

The Ordinary Least Square (OLS) estimators $\hat{\gamma}$ and $\hat{\beta}$ are consistent if equation (1) satisfies the assumption that the residual is not correlated with any other regressors. But this assumption is violated in the model with lagged dependent variable ($\gamma \neq 0$). Consider a two-period time lag:

$$y_{i,t-1} = \gamma y_{i,t-2} + x_{it}\beta + v_{i,t-1}, \; i = 1, \dots, N, t = 1, \dots, T, \qquad (2)$$

Since the unobserved effect c_i appears in both v_{it} and $v_{i,t-1}$, $y_{i,t-1}$ is correlated with v_{it} causing serial correlation in the error terms ($corr(v_{it}, v_{is}) \neq 0, for\ t \neq s$), which seriously biases the OLS estimator.

5.3.2 Fixed Effect (FE) and Random Effect (RE) Estimators

Standard panel data estimators either treat c_i as a fixed parameter (rendering it orthogonal to explanatory variables) or as a random parameter drawn from a specific distribution (with unknown parameters). Generalized Least Squares (GLS) is used in FE and RE estimations to correct for the serial correlated errors as well as for panel heteroskedasticity. Even standard panel data estimators, however, are not appropriate for estimating model (1) with the correlation between the lagged dependent variable ($y_{i,t-1}$) and the component disturbance (v_{it}), even if it is assumed that v_{it} is not itself autocorrelated.

For the fixed effect estimator, the *within* transformation[9] wipes out the unobserved effect, c_i (Wooldridge 2002, page 267). Therefore, without lagged dependent variable, fixed effect estimator is the best linear unbiased estimates (BLUE) as long as u_{it} is normally distributed with

[9] $y_{it} - \bar{y}_i = (x_{it} - \bar{x}_i)\beta + u_{it} - \bar{u}_i$, where $\bar{y}_{i,t} = \sum_{t=1}^{T} y_{i,t}/T$, $\bar{x}_{i,t} = \sum_{t=1}^{T} x_{i,t}/T$, $\bar{u}_{i,t} = \sum_{t=1}^{T} u_{i,t}/T$

mean 0 and variance matrix $\sigma_{u_{it}}^2 I_{NT}$. In the dynamic model, however, $\bar{u}_{it}$ contains $u_{i,t-1}$ which is correlated with lagged dependent variable $\left(y_{i,t-1} - \bar{y}_{i,t-1}\right)$ where $\bar{y}_{i,t-1} = \sum_{t=2}^{T} y_{i,t-1}/(T-1)$ will be correlated with $(u_{it} - \bar{u}_{it})$ even though u_{it} are not serially correlated. Therefore, fixed effect estimation generates biased coefficients. Nickell (1981) derives an expression for the bias when there are no exogenous regressors, showing that the bias approaches zero as T approaches infinity. Thus, the fixed effect estimator only performs well when $T \rightarrow \infty$. But in our analysis, N is large (100 counties) and T is fixed (16 years), so the within estimator is biased and inconsistent. For random effect estimator, quasi-time demanded transformation $\left(y_{i,t-1} - \theta \bar{y}_i\right)$ will correlate with $\left(u_{i,t-1} - \theta \bar{u}_i\right)$[10], so the random effect GLS estimator is also biased in the dynamic panel model (Wooldridge 2002 chapter 10).

5.3.3 Anderson-Hsiao Estimators

Hsiao (1986) develops a maximum likelihood estimator for first-order autoregression, AR(1), panel data. The distribution of dependent variables, however, depends upon the initial conditions $y_{i,1}$. A wide variety of likelihood functions with different assumptions about the nature of the initial conditions can be inconsistent when the initial conditions process is mis-specified. In addition, many previous studies (Balestra and Nerlove 1966, Maddala 1971, and Nerlove 1971) have demonstrated poor performance of maximum likelihood estimation (MLE) for panel data that has a large number of cross-sectional units, but only a few time periods.

Anderson and Hsiao (1981, 1982) introduce an instrumental variables estimator for dynamic panel data models which requires much weaker assumptions about the initial conditions. It removes the unobserved effect by first differencing and then using $(y_{i,t-2} - y_{i,t-3})$ or $y_{i,t-2}$ as an instrumental variable (IV) for $(y_{i,t-1} - y_{i,t-2})$:

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[10] $\theta = 1 - \left[\frac{\sigma_u^2}{\sigma_u^2 + T\sigma_c^2}\right]^{\frac{1}{2}}$

$$y_{it} - y_{i,t-1} = \gamma(y_{i,t-1} - y_{i,t-2}) + \beta(x_{it} - x_{i,t-1}) + (u_{it} - u_{i,t-1}) \qquad (3)$$

The variables $(y_{i,t-2} - y_{i,t-3})$ and $y_{i,t-2}$ are correlated with $(y_{i,t-1} - y_{i,t-2})$ but neither of them are correlated with $(u_{it} - u_{i,t-1})$, as long as u_{it} are not self serially correlated[11]. Thus, the Anderson-Hsiao estimator can provide for consistent estimation of γ and β (Hsiao 1986). The standard application of the instrumental variables technique can be found in Wooldridge (2002) (page 83-86). Arellano (1989) provides evidence that the use of differences instruments, $(y_{i,t-2} - y_{i,t-3})$, has a singularity point and very large variances over a range of parameter values, particularly, when $\gamma \to 1$. The estimator that uses levels instruments, $y_{i,t-2}$, has no singularities and much smaller variances, which is preferred in our application. For simplicity, we transform the model (3) to:

$$y_{it} - y_{i,t-1} = \delta(w_{it} - w_{i,t-1}) + (u_{it} - u_{i,t-1}) \qquad (4)$$

where $\delta = (\gamma\ \beta)'$ and $w_{it} = (y_{i,t-1}\ x_{it})'$.

The instrumental variables estimators of Anderson-Hsiao is given by

$$\hat{\delta} = (\sum_{i=1}^{N}\sum_{t=3}^{T} z_{it}\Delta w_{it}')^{-1} \sum_{i=1}^{N}\sum_{t=3}^{T} z_{it}\Delta y_{it}$$

where

$z_{it} = (y_{i,t-2}\ \Delta x_{it})'$ denotes the instrument set as period t ($\Delta x_{it} = x_{it} - x_{i,t-1}$).

$\Delta w_{it} = w_{it} - w_{i,t-1}$

$\Delta y_{it} = y_{it} - y_{i,t-1}$

The asymptotic variance matrix of $\hat{\delta}$ is:

[11] See later discussion of the Arellano-Bond test for first-ordered serial correlation.

$$Avar(\hat{\delta}) = H^{-1}FH^{-1}$$

where

$H = (T-2)E(z_{it}\Delta w_{it}^{'})$,

$F = \sigma_u[2(T-2)E(z_{it}z_{it}{'}) - (T-3)E\left(z_{it}z_{i,t-1}{'}\right) - (T-3)E\left(z_{i,t-1}z_{i,t}{'}\right)]$.

5.3.4 Arellano-Bond Estimators

Building upon the innovative work by Anderson-Hsiao, Arellano and Bond (1991) use a Monte Carlo experiment to gauge the performance of the Anderson-Hsiao IV estimator against Generalized Method of Moments (GMM). They find GMM improves the efficiency of estimation because it uses all available lagged dependent variables and lagged exogenous regressors as instruments – information that the Anderson-Hsiao IV estimator neglects[12] (Baltagi 2005, page 136-137). The GMM is a generic method for estimating parameters in the model, where the parameter of interest is finite-dimensional, whereas the full shape of the distribution of the data may not be known, and therefore maximum likelihood estimation is not applicable. The first-differenced GMM estimator for the AR(1) model has been discussed in previous research (Holtz-Eakin, Newey and Rosen 1988, Arellano and Bond 1991).

Let transformed residuals satisfy the population moment condition: $E[Z_{it}^{'}\Delta u_{it}] = 0$ (t= 2…T), where Z_{it} is a set of instrumental variables; Δu_{it} is differences of random disturbances. For notational efficiency, we stack the time period t by following transformation:

$$Z_i = \begin{bmatrix} y_{i,1} & \Delta x_{i,3} \\ \vdots & \vdots \\ y_{i,T-2} & \Delta x_{i,T} \end{bmatrix} \qquad X_i = \begin{bmatrix} y_{i,2} & \Delta x_{i,3} \\ \vdots & \vdots \\ y_{i,T-1} & \Delta x_{i,T} \end{bmatrix} \qquad Y_i = \begin{bmatrix} \Delta y_{i,3} \\ \vdots \\ \Delta y_{i,T} \end{bmatrix}$$

[12] The panel data structure provides a large number of instrumental variables in the form of both lagged endogenous and exogenous variables.

$$Z = \begin{bmatrix} Z_1 \\ \vdots \\ Z_N \end{bmatrix} \quad X = \begin{bmatrix} X_1 \\ \vdots \\ X_N \end{bmatrix} \quad Y = \begin{bmatrix} Y_1 \\ \vdots \\ Y_N \end{bmatrix}$$

Therefore, the sample analogue of the population moment condition ($E[Z_{it}^{'}\Delta u_{it}] = 0$) that can enter the construction of a GMM estimator is:

$$\frac{1}{N} Z'(Y - X\delta) = 0 \qquad (5)$$

The optimal GMM estimator is then given by:

$$\hat{\delta}_{GMM} = (X^{'}ZA_N Z^{'}X)^{-1} X^{'}ZA_N Z^{'}Y$$

Arellano and Bond (1991) suggest using

$$A_N = (\frac{1}{N}\sum_{i=1}^{N} Z_i^{'} H Z_i)^{-1}$$

to produce the initial consistent estimator (one-step GMM estimator), where:

$$H = \begin{bmatrix} 2 & -1 & 0 & 0 & \cdots & 0 \\ -1 & 2 & -1 & 0 & \cdots & 0 \\ 0 & -1 & 2 & -1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 2 \end{bmatrix}$$

(H is a (T − 2) square matrix with 2 on the main diagonal, -1 on the first off-diagonals and zeros elsewhere.)

A consistent estimator of the asymptotic covariance is given by:

$$Est.Asy.Var\left[\hat{\delta}\right] = (X^{'}ZV_N Z^{'}X)^{-1}$$

where $V_N = (\sum_{i=1}^{N} Z_i'(\Delta u_i)(\Delta u_i)' Z_i')^{-1}$

Under heteroskedasticity of the disturbances, the two-step GMM estimators for the first-differencing can be obtained by change the A_N to:

$$(\frac{1}{N}\sum_{i=1}^{N} Z_i^{'}\Delta\hat{u}_i\Delta\hat{u}_i^{'}Z_i)^{-1}$$

where the $\Delta\hat{u}_i$ are the estimates of the first-differenced residuals.

The one-step and two-step GMM estimators are asymptotically equivalent for the first-difference estimator (Arellano and Bond 1991). Results from simulation studies suggest the two-step GMM estimator produces efficiency gains with heteroskedastic disturbance, but this estimator has the disadvantage of relatively slow convergence to its asymptotic distribution. The asymptotic standard errors associated with the two-step GMM estimator in finite sample case can be seriously biased downwards. Several previous applied studies focus on the results from one-step estimator, since it appears to be more reliable for making inferences in small samples (Arellano and Bond 1991, Baltagi 1995, Blundell and Bond 1998, Wawro 2002). With this in mind, we prefer to report the results for the one-step GMM estimator[13].

5.3.5 Testing the Specification

The consistency of estimation in the previous discussion depends on the assumption that the random disturbance u_{it} is serially uncorrelated. In equation (1), if u_{it} is first-ordered serial correlation ($u_{it} = \rho u_{i,t-1} + \varepsilon_{it}$, $\varepsilon_{it} \sim i.i.d$), then the Δu_{it} in equation (3) is second-ordered

[13] In this chapter, our studies have found that one-step estimator outperforms the two-step estimator in terms of producing a much smaller standard errors of the estimates.

serial correlated[14]. As a result, $y_{i,t-2}$ are no longer valid instrumental variable for $(y_{i,t-1} - y_{i,t-2})$ in equation (4). Therefore the consistency of the GMM estimator relies on that there is no second ordered serial correlation in u_{it}. Arellano and Bond (1991) propose a test for the hypothesis that there is no second-order serial correlation in the random disturbance. The test statistic can be found in equation (8) and (9) of Arellano and Bond (1991, page 282). The shortcoming of this test is that it is defined only if $t > 4$.

When $t > 3$, the model is overidentified[15], Arellano and Bond (1991) use Sargan's test of over-identifying restrictions in the moment condition, $E[Z_{it}^{'}\Delta u_{it}] = 0$. The function is given by:

$$s = \hat{u}'Z\left(\sum_{i=1}^{N} Z_i^{'}\hat{u}_i\hat{u}_i^{'}Z_i\right)^{-1} Z'\hat{u} \sim \chi^2_{(p-K-1)}$$

where $\hat{u}$ is the vectors of estimated first differenced residual for all i and T. p is the number of columns in vector of instrumental variables, Z. $K - 1$ is the number of explanatory variables. s has an asymptotic chi-square distribution under the null hypothesis that the moment conditions are valid.

5.4 Data

The list of CRS communities and their 2008 CRS scores are available on the FEMA website (http://www.fema.gov/pdf/nfip/manual200805/19crs.pdf). The structure of NFIP rests on a multi-jurisdictional configuration which allows for participating counties, towns, and cities. Therefore, the extent and timing of enrollment in CRS for county and municipalities within the county may vary. Since the local CRS score reflects the population directly benefiting from mitigation efforts, we population-weight their CRS scores and calculate an aggregated score for

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[14] $\Delta u_{it} = u_{i,t} - u_{i,t-1} = \rho u_{i,t-1} + \varepsilon_{it} - \rho u_{i,t-2} - \varepsilon_{it} = \rho\left(u_{i,t-1} - u_{i,t-2}\right)$

[15] In an overidentified equation, the number of instrumental variables is greater than the number of endogenous explanatory variables.

the county and nested municipalities as a single unit. This calculation was performed for all 100 NC counties (and nested municipalities) for 1995 to 2010 (see Appendix 1 for details).

The table 5.1 presents a summary of the variables to be used in our analysis. The explanatory variables are organized under three broad categories. First, previous flood events were collected from National Climate Data Center (NCDC) and are proposed to account for the severity of community flood hazard experience. We postulate that greater historical experience with floods will motivate more stringent hazard mitigation, increasing the CRS score. The first different GMM model requires the use of time-variant data. As such, we use a time variant risk index to account for risk characteristics of each county. We created a risk index variable by multiplying annual precipitation with the percentage of land in the local Special Flood Hazard Area (SFHA). The average annual precipitation (1995-2010) at weather stations within the county is provided by the State Climate Office of North Carolina. The digital flood hazard maps in the North Carolina Floodplain Mapping program are available only back to 2008. Given the rainiest and more floodplain counties face a higher probability of riverine and flash floods, which could be a catalyst for local flood hazard mitigation, we expect county with higher risk index to be more likely to engage in hazard mitigation due to greater benefit of the CRS credible projects accruing to more local residents. But since counties with large floodplains require more resources to conduct rigorous flood mitigation planning, higher risk index could reduce the political incentive for intervention.

Next, we include five variables reflecting local capacity for hazard mitigation and competing priorities. Data on per capita county property taxes, which is collected from NC Association of County Commissioners Budget & Tax Survey, represents local government financial resources available for hazard mitigation projects. We expect counties with greater tax revenue to be more likely to engage in flood hazard mitigation. In local government, the available funding for emergency management and hazard preparedness are important to the community's floodplain management staff and to its participation in the CRS. We expect the counties with greater percentage of emergency management expenditure over general government expenditure are more likely to improve their CRS score. Competing priorities, on the other hand, may crowd out hazard mitigation. The benefits of hazard mitigation are only realized after a disaster occurs and are difficult to quantify, but the costs are incurred immediately and are easily calculated. Therefore, other problems, such as job creation, control of crime, and improving the quality of education, usually garner more attention than hazard mitigation projects. The pressing needs of such "here and now" issues may attract more time, money, and other resources and can crowd out hazard mitigation initiatives (Prater and Lindell 2000). We account for these other potential county policy priorities in the regression models. We collected the unemployment rate from North Carolina Department of Commerce. The data use the ratio of enrolled students to instructional staff in county public school to measure local school quality (Card and Krueger 1992). These data were collected from NC Department of Public Instruction. The crime rate is a proxy for the competing concerns over criminal activity in the county; the number of reported crimes (including murder, forcible rape, robbery, aggravated assault, burglary, larceny, and motor vehicle theft) per household was derived from NC Department of Justice.

Lastly, we include factors that account for the effect of community characteristics on local hazard mitigation. We include the population density, median household income, a migration dummy variable, and the percentage of senior citizens. Population density is calculated as the total population in a county divided by the county area in miles. Population data is collected from U.S. Census. The data on land area of each county is derived from averaging 1990 and 2000 U.S. census data. We expect more densely populated areas to be more likely to engage in hazard mitigation due to greater benefit of flood protection accruing to more local residents. Annual data on median household income is not complete from U.S. Census at county level. Thus, we use estimates from the Department of Housing and Urban Development (HUD), which are prepared as part of the process of updating eligible income limits for the community development program. Median household income provides a proxy for the level of individual wealth. We conjecture that wealthier communities may exhibit a greater demand for hazard mitigation, but wealthier households may put less pressure on local governments for hazard mitigation since they are better able to afford individual mitigation measures and insurance.

In previous studies of CRS, neither Brody et al (2009) nor Posey (2009) include age structure or migration trends among their socio-economic variables. While a public's willingness to support and contribute to the mitigation activities may depend on the local severity of risk and the community's commitment to dealing with the problem (Burby 1998), the vulnerability of elders as a group could be an important factor in overall vulnerability assessment which may increase the likelihood of local hazard mitigation. North Carolina, however, has become a popular retirement destination due to the state's varied terrain, moderate climate, reasonable housing prices, and special tax exemptions for military and other federal employees' retirement pay. This has led to increasing numbers of immigrating retirees, many of which may have limited experience with flood hazards. Thus, our expectations of the impact of proportion of senior citizens and migration on hazard mitigation activities are ambiguous. Census data on age of migrants is not available. We collected data on the senior population from U.S. Census. Data estimates of net migration are derived from NC Office of the Governor.

5.5 Result

Brody, et al. (2009) examine policy learning for flood mitigation as reflected in CRS scores in Florida counties from 1999 to 2005. Specifically, they track annual point totals for the four CRS mitigation series for 52 of the 67 Florida counties that exhibit some level of voluntary participation in the CRS. They use population-adjusted measures of CRS points and regression covariates to account for both participating counties and nested municipalities, and examine the influence of hydrologic conditions, flood disaster history, socioeconomic, and human capital controls on CRS points. Their study use feasible GLS (FGLS) regression models with a panel-specific AR(1) correlation for correcting the groupwise heteroskedasitcity and serial autocorrelation (see Appendix 2 for the description of FGLS). First, without considering state dependence, we repeat Brody et. al's work using the variables described in Table 5.1. The specification of the empirical model is given as follows:

$$\begin{aligned}\mathrm{Log}(CRS_{it}) = {} & \beta_0 + \beta_1 Flood_{it} + \beta_2 \mathrm{Log}(Risk\_Index_{it}) + \beta_3 \mathrm{Log}(Tax_{it}) + \beta_4 \mathrm{Log}(Staff_{it}) \\ & + \beta_5 \mathrm{Log}(Crime_{it}) + \beta_6 \mathrm{Log}(unemployment_{it}) + \beta_7 \mathrm{Log}(Student\_Teacher_{it}) \\ & + \beta_8 \mathrm{Log}\left(Population_{Density_{it}}\right) + \beta_9 \mathrm{Log}(Senior_{it}) + \beta_{10} \mathrm{Log}(Income_{it}) \\ & + \beta_{11} \mathrm{Log}(Migration_{it}) + c_i + \lambda_t + u_{it} \qquad (6)\end{aligned}$$

We take natural logarithm of CRS scores and continuous dependent variables so that coefficient estimates indicate the percentage change of the CRS score in response to a one percentage change in the explanatory variables. It is difficult to measure the goodness-of-fit of the model when the sample data are generated by the general linear regression model. The FGLS estimator is simply the OLS estimator applied to a transformed regression that purges the heteroscedasticity and/or autocorrelation. We report the squared correlation coefficients between actual and predicted levels of the dependent variable. This squared correlation measure is equivalent to the standard R^2 in an OLS regression, and is recommended as a goodness-of-fit measure for instrumental variable regressions by Windmeijer (1995). (We also use same measurement for GMM). The transformed R^2 ranges from 0 to 1 with higher values indicating better fit. We also report two Wald statistics. The first is a test of the joint significance of the time dummy variables, while second is a test of the joint significance of all explanatory variables. Both tests are asymptotically distributed as chi-square. The significant result from Wald test of time dummy variables indicated that the time shocks play a significant role in local hazard mitigation. The unobserved effect can be measured as $\rho = \frac{\sigma_c^2}{1+\sigma_c^2}$, ($\sigma_c^2$ is the variance for the time invariant unobservable effect) (Wooldrige 2002, Greene 2002). Standard statistical packages reports estimated rho ($\hat{\rho}$), which allows for straightforward testing of the presence of unobserved, time-invariant cross-sectional effects. The statistically significant rho parameter ($\hat{\rho} = 0.83$) indicates the existence of an unobserved time invariant effect at the cross-sectional level. As shown in the Table 5.2, the signs for the covariate parameters, which indicate the direction of impact on probability of participation in CRS, are consistent with Brody et al.'s work.

We then introduce the lagged dependent variable which is added into the equation (6). The equation (7) is a dynamic panel data model:

$$\begin{aligned}\text{Log}(CRS_{it}) = \beta_0 &+ \beta_1 Log(CRS_{i,t-1}) + \beta_2 Flood_{it} + \beta_3 \text{Log}(Risk\_Index_{it}) + \beta_4 \text{Log}(Tax_{it}) \\ &+ \beta_5 \text{Log}(Staff_{it}) + \beta_6 \text{Log}(Crime_{it}) \\ &+ \beta_7 \text{Log}(unemployment_{it}) + \beta_8 \text{Log}(Student\_Teacher_{it}) \\ &+ \beta_9 \text{Log}\left(Population_{Density_{it}}\right) + \beta_{10} \text{Log}(Senior_{it}) + \beta_{11} \text{Log}(Income_{it}) \\ &+ \beta_{12} \text{Log}(Migration_{it}) + c_i + \lambda_t + u_{it} \qquad (7)\end{aligned}$$

We use first differences of the dependent variable in order to eliminate the individual time-invariant effect c_i. The Arellano Bond estimation then uses the GMM with lagged values of the endogenous variable ((Log($CRS_{i,t-3}$)) as instruments. The results of the one-step Arellano-Bond Difference GMM estimation are presented in Table 3. The result of Arellano-Bond test for zero autocrorrelation in first-differenced errors shows that there is no second order serial correlation in u_{it}, as desired ($\text{p}-\text{value}_{\text{AR}(1)} = 0.026;\ \text{p}-\text{value}_{\text{AR}(2)} = 0.630$). Concerning the instruments, the Table 5.2 also reports the Sargan statistic, which tests the over-identifying restrictions. The validity of $y_{i,t-2}$ as instruments in the equation is not rejected by the Sargan test of overidentifying restrictions in the moment condition at 1% significant level.

Comparing FGLS and GMM in table 3, the signs for the covariate parameters are consistent across both models. While not directly comparable to the transformed R-square, both R-squares indicate fairly good fit for the models R-sq=28% for FGLS and pseudo R-sq=39% for GMM. The number of statistically significant covariates increases from seven to ten when we move from FGLS to the more appropriate GMM. Concerned with the dynamic mechanism in policy learning, our explanation of the results focuses primary attention on the result of GMM one-step, while making some comparisons with FGLS as a more basic model.

The estimated coefficient on the lagged dependant variable is statistically significant at 1% in GMM. We find a highly significant impact of previous CRS score on the current local CRS point improvement ($\beta_{Log(CRSi,t-1)} = 0.6120$). For example, a one percent increase in the previous CRS points is associate with an increased change in current CRS points by approximately 0.612 percentage. This result supports the theory that the most important influence in policy learning is past policy itself and established policy legacies (Brody 2003). Holding flood experience, hydrological risk factors, and level of financial resources constant, once the local governments regulate their floodplains beyond the minimum required by the NFIP, it tends to carry on incrementally year by year, despite potential changes in staff changes and shifts in local political regimes. This suggests a commitment amongst some local governments to high levels of floodplain management activities that can benefit the entire community. Furthermore, we note that marginal increases in CRS points are relatively more difficult to achieve when initial points have already been obtained, since it generally requires increased resource allocation and continued political support and.

We consider both models to discuss the impact of the flood experience on CRS score improvement. We find previous one year flood events have statistically significant and positive effect on CRS creditable activities for FGLS and GMM; results indicate that an additional flood event in the previous year increases the change in CRS score by 0.96% and 1.11% for the FGLS and GMM, respectively. We did try using different time lags for flood experience (e.g., two- and three-years), but found no statistically significant effects for more distant flooding events. Landry and Li (2012) demonstrate that long term experience with flood events appears to encourage local hazard mitigation project adoption (as reflected in CRS participation). The effects they found for historical flooding may indicate that certain communities that had experienced hazards were more likely to enroll in CRS at the program inception. However, with established mitigation regulations, the immediate aftermath of hazard events can open up a "window of opportunity" for local authorities to focus attention on hazard mitigation and continue to obtain additional credits for hazard mitigation activities. FEMA and state agencies should take a more active role in demonstrating successful hazard mitigation programs after local flood events. This information sharing project could help local governments understand the potential benefits of the flood hazard mitigation projects, which could strengthen their own flood protection programs.

We account for potential variability in flood risk across counties with a risk index which is created by multiplying annual precipitation with the percentage of local Special Flood Hazard Area (SFHA). Our expectations are that higher risk factors will be associated with greater improvement of local mitigation. However, results indicate that counties with greater average rainfall and a greater proportion of SFHA exhibit significantly lower flood hazard mitigation activities within the CRS system. Focusing on GMM results, a one percentage point increasing in the risk index decreases the change in the score by 0.0088%. One interpretation of this result rests on recognizing that the larger the proportion of floodplain land in the county, the less land available for the potential development. From an economic and public policy perspective, mitigation activities in these counties may require more resources given the level of vulnerability, and since more land is in the floodplain, interventions in economic development within this area may be politically less desirable. The estimates from FGLS are roughly equivalent – in both cases the estimated effects are relatively small. Given the composition of the risk index, it is impossible to isolate the effects of precipitation from the percentage of land in the

SFHA. The impact of different vulnerability measures on mitigation activities remains an important area for future research.

The estimated effect of per capita property tax levy exhibits a positive and statistically significant sign in both FGLS and GMM, which abides our expectations that financial capacity would increase mitigation policy adoption and implementation. Results of the GMM model indicate that one percentage increase in average property tax per capita increases the change in CRS score by 0.1872%, while the FGLS puts the marginal effect at 0.1226%. These findings imply that flood hazard mitigation is more likely to occur in wealthier districts with greater tax revenue and that poorer districts with less financial capacity may be more vulnerable to flood hazard. In addition, wealthier districts might also be expected to have more valuable building stock and thus more incentive to protect these assets. The results also indicate that one percentage increase in funding available for emergency management planning increases the change in CRS score by 0.0309% in GMM, or 0.023% in the FGLS. Continued financial support of emergency management and public safety likely reflects a political commitment to hazard mitigation planning and thus strengthens flood mitigation policy.

For competing local public policy priorities, we use local unemployment rate to account for general local economy condition, student-teacher ratio to account for local public school quality, and crimes per household to account for public safety. Our previous expectations were that the unemployment issues, school quality, and crime could be strong competitors with hazard mitigation projects for limited local financial resources. The estimated coefficients for all three variables exhibit expected negative signs, but their significance levels are mixed. The estimated coefficients for crime density are significant; a one percentage increase in crime density decreases the change in CRS score 0.0203% in GMM (0.0306% for FGLS). According to the results of GMM, increasing the unemployment rate by one percentage decreases the change in CRS score by 0.065%. Compared with other crowding-out factors, local economic conditions appear to play an important role for influencing the allocation of financial resources (relative to flood hazard mitigation). The influence of student teacher ratio on CRS score is negative but not statistically significant in both models. There is much greater variability in teacher and student ratio at the school district, which may explain the lack of significance of this covariate in our models. Future research should attempt to refine our approach (with better data) and explore the extent to which other local problems (transportation and economic development) crowd out investments in hazard mitigation.

Holding flood experience, risk factors, and level of resources constant, the influence of population-density on likelihood of participation in CRS is positive but not statistically significant in the GMM model. Our prior expectations were that counties with more residents might have higher demand for mitigation projects that can lower flood damage. According to the FGLS results, increasing population-per-square-mile by one percent increases the change in CRS points by 0.6245%. This could indicate a pure benefit effect (as more household exposed to risk increases the benefit of mitigation), but could also reflect greater local government financial capacity (tax base). The insignificant result in GMM may be due to correlation between crime and population density (*Corr (crime, population density) =0.9152*). As benefits of hazard mitigation are likely greater in densely populated area, a better proxy for population would be the number of local housing units (for which annual data are unavailable).

Community-wide levels for income may shape the type and speed of learning from the flood risk mitigation efforts (Brody, et al 2009). Our results show that county CRS-creditable activities are sensitive to median household income levels. For each model, the estimated coefficient for *Log(Income)* is positive and statistically significant at 5% level, and it has a very strong impact on the CRS score. Increasing the median household income by one percentage increases the change in CRS score by 0.3689% in the GMM (0.3836% in FGLS). This result suggests that household level financial capital in the community may influence the speed of learning and lead to improvements in mitigation efforts.

Landry and Li (2012) show evidence that the proportion of senior citizens in a community has significant and negative impact on probability of participation in CRS. They argue the impact may be induced by a tremendous influx of immigrating retirees. However, the results in table 3 show that the estimated coefficients of *Log(Senior)* and *Migration* are positive and significant in GMM, but both are insignificant in FGLS. The change in CRS score increases 0.1683% for a 1% increase in proportion of senior citizens; we find similar results for the migration dummy – that the change in CRS score is 0.028% higher in counties with a positive net migration relative to counties with a negative net migration rate. Thus, our results do not support the counter-intuitive findings of Landry and Li (2012) regarding the influence of senior citizens nor the potential explanation of immigrating retirees.

5.6 Conclusions

The suffering from flooding events can be reduced by appropriate floodplain regulation and hazard mitigation planning. This chapter discussed how to use dynamic panel data models as a powerful tool to better understand how local communities adopt and improve their flood mitigation policies. Flooding, like other natural disaster such as hurricane and earthquake, reoccurs over time. Therefore, hazard mitigation plans and policies need to be updated and adjusted by policy makers over time in order to adapt to the uncertain environment. The authorities have the opportunity to recognize the effectiveness of previous policies and improve their strategies as well. Brody, et al. (2009) conceptualize this policy adjustment in the flood risk management as policy learning - "*a change in policy or the strength of a policy in response to flood events or some other factors*". This chapter focuses on one specific FEMA mitigation program-Community Rating System which offering reductions in flood insurance rates in exchange for local flood hazard mitigation efforts that exceed minimum standards of floodplain management set by the National Flood Insurance Program.

We describe the course of CRS creditable activities chosen by the local authorities as a policy learning process. This policy learning reflects political dominance that leads to the adoption of new mitigation projects and regulations into local mitigation policy design, but also a consideration of substantive policy processing and feedback of flood risk management experience. While there is no shortage of theories about policy learning, all postulates are in agreement on the principle impacts of previous policy efforts on current goals and objectives that policy makers pursue; the existence of dynamic nature can be accounted for in empirical analysis with suitable econometrics modeling techniques. In this chapter, we present a study of the determinants of the policy learning related to flood hazard mitigation. The analysis is preformed using data pertaining to 100 NC counties for the period 1995-2010 in a dynamic panel framework. The dynamic panel data model includes lag of dependent variable (aggregated CRS score) to accommodate the theory of state in an intuitive manner. We applied the GMM approach and instrumental variables to deal with endogeneity issues.

This chapter provides some important insights for policy learning related to the flood mitigation. The previously established mitigation policy (CRS score) has great impact on subsequent policy change. The local authorities could draw lessons from their previous policy design and summarize the strengths of local mitigation projects while minimizing shortcomings.

The creation of “policy legacies” is an underlying catalyst for policy learning (Brody 2003). Therefore, FEMA and state agencies could take a more active role in providing a stronger framework for grant-in-aid and technical assistance to help local communities initiate mitigation planning. Once the strengthen policy is adopted, local mitigation activities may perpetuate due to self learning which can help ensure the long term development of resilient communities.

While our results demonstrate that the change in the current policy is strongly influenced by previous rounds of policy development, the analysis suggests that policy learning is in fact a more complex phenomenon in that it also responds to some environmental and social stimulus, such as vulnerability measures, tax revenues, population, and etc. Although, our study provides evidence that local mitigation policy learning exhibits a change-inducing mechanism, it is difficult to include as many environmental and social factors as we would like since the first-difference structure of the GMM model requires the time-variant data, and longitudinal data on covariates such as annual precipitation, education level, and housing density are not readily available at county levels. When such data become available, future research should also attempt to refine our approach and explore the extent to which other local condition affect investments in hazard mitigation.

Table 5.1: Data Description for 100 Counties in North Carolina, 1995-2010

Variable	Description	Mean	Std Dev
CRS	Population weighted CRS score for all community in each county (1995-2010)[16]	192.511	395.601
	Risk Variables		
Flood	Total number of flood events in previous year in county (1995-2010)	0.357	0.802
Risk-Index	Annual precipitation multiplied by percentage of 2008 SFHA in county	7.114	8.173
	Resources Variables		
Tax	Property tax levy per capita in each county (in thousand dollars-year 2000 inflation adjusted dollars) (1995-2002)	0.476	0.195
Staff	Percentage of government expenditures for emergency management and other public safety out of total expenditure (%)	15.519	4.735
Unemployment	Unemployment rate in county (%) (1995-2010)	5.961	2.618
Student-Teacher	Students and teachers ratio in public schools in previous year (1995-2010)	13.805	1.745
Crime	Reported crime and population ratio in county (1995-2010)	0.036	0.019
	Social Variables		
Population-Density	Number of population per square mile (1995-2010)	176.614	220.350
Income	Median household income (in thousand dollars-year 2000 inflation adjusted dollars)(1991-2002)	41.759	8.089
Migration	Dummy variable, equal one for positive migration, equal zero otherwise	0.825	0.380
Senior	Percentage of senior citizens (65 years and over) out of total population (%) (1995-2010)	0.141	0.036

Note: The total number of the observation is 1600

[16] See Appendix 1 for detail.

Table 5.2: Estimation Result for FGLS and GMM One-Step

	FGLS		GMM One-Step	
Variables	**Coef.**	**P-value**	**Coef.**	**P-value**
	(S.E.)		**(S.E.)**	
Log($CRS_{i,t-1}$)			0.6120	0.000
			(0.0273)	
Flood	0.0096	0.014	0.0110	0.000
	(0.0036)		(0.0014)	
Log(Risk-Index)	-0.0118	0.015	-0.0088	0.043
	(0.0052)		(0.0043)	
Log(Tax)	0.1206	0.001	0.1872	0.000
	(0.0379)		(0.0208)	
Log(Staff)	0.0230	0.182	0.0309	0.000
	(0.0172)		(0.0062)	
Log(Crime)	-0.0306	0.08	-0.0203	0.000
	(0.0175)		(0.0052)	
Log(Unemployment)	-0.0402	0.095	-0.0657	0.000
	(0.0240)		(0.0076)	
Log(Student-Teacher)	-0.0177	0.688	-0.0297	0.140
	(0.0442)		(0.0201)	
Log(Population-Density)	0.6245	0.017	0.5353	0.486
	(0.2611)		(0.0769)	
Log(Income)	0.3836	0.051	0.3689	0.000
	(0.2008)		(0.0669)	
Migration	0.0079	0.299	0.0208	0.000
	(0.0076)		(0.0056)	
Log(Senior)	0.3216	0.216	0.1683	0.012
	(0.2601)		(0.0670)	
Constant	0.4104	0.775	2.7789	0.000
	(1.4383)		(0.4023)	
Time Dummies	Included		Included	
Wald time dummies	40.45	0.0004	490.68	0.000
(df=15)				
Wald joint significance	77.76	0.000	395.32	0.000
(df=11, 12)				
R^2	0.28		0.39	
First-order serial correlation			-2.23	0.026
Second-order serial correlation			0.48	0.630
Sargan Test			456.48	0.000
Number of Observation	1482		1376	
Note: Standard errors in parentheses				

Chapter 6: Conclusions

While dynamics of weather play an important role in recent growth of damaging floods in the US, intensive development in the floodplain and extensive population growth in low lying coastal areas have increased human beings' exposure to flood hazards. The American Housing Survey estimates that 4.6% of new houses (595,000) built between 1999 and 2007 were located in the floodplain. Data from US Census Bureau indicate that more than half of the US population lives in the coastal zone, even though coastal counties constitute only about one fourth of the countries landmass. Despite the ostensible elevation of risk, studies on individual mitigation behavior indicate that few property owners voluntarily adopt measures to reduce their potential losses from future catastrophes (Kunreuther 1996; Kunreuther and Roth 1998; Siegrist and Gutscher, 2008; Mileti 1999).

As such, local governments can play a critical role in flood hazard mitigation (Prater and Lindell 2000). Scholars generally recognize two types of hazard mitigation that can be adopted for flood risk. Traditional flood damage mitigation focused on structural engineering solutions, such as dams, levees, and channel improvements. FEMA (1986) estimates over $7 billion in public monies have been spent on large scale flood control works between the mid-50s and mid-80s. Zahran et al. (2008) conclude that an increase in the number of Texas dams decreased the odds of death or injury due to flood by 22.6 percent. Average annual flood property damage is rising continually, however, and estimated to exceed $3 billion in coming years. The overwhelming expense and adverse environmental effects of structural flood mitigation works have lead to more emphasis being place on smaller scale non-structural mitigation methods. Non-structural measures include zoning ordinances, building codes, flood warning systems, emergency planning, flood insurance, and so forth. Many of these measures have elements of local public goods, in that they provide benefits for an entire community and agents in the community are not excluded once they have been made available. Our study focuses primary attention on non-structural mitigation, as recognized by the Community Rating System of the National Flood Insurance Program.

In order to motivate flood insurance purchase and promote flood hazard awareness and mitigation, the Community Rating System (CRS) of National Flood Insurance Program (NFIP), credits floodplain management activities and awards flood insurance premium discounts. Limiting its potential effectiveness, CRS has been marked by a lack of active participation since its inception. As of January 2008, 1080 communities, represents only 5% of all the NFIP communities, had enrolled in CRS. Of the 469 NFIP communities in North Carolina, only 75 (slightly over 15%) have a CRS score that is less than 10 (implying that they have initiated activities to improve awareness and reduce risk and applied for credit). Since CRS uses standardized quantitative measures for representing local hazard mitigation activities, it provides an excellent source of information for empirical analysis of community hazard mitigation decisions. The objective of this dissertation is to provide empirical evidence related to community decisions involving incentive-based flood risk mitigation projects. Our overarching hypothesis is that community characteristics can influence the local government decision-making process and the amount of hazard mitigation that takes place locally. In addition, the overall level of risk in the community and other day-by-day issue such as crime and school quality should influence hazard mitigation. Higher perceived risk should motivate more mitigation, all else being equal. We use these intuitive propositions, built upon previous literature, to structure our empirical analysis. Through an improved understanding of CRS, state governments and FEMA can better encourage participation in the CRS and similar programs in order to provide for better protection from natural hazards. It also allows for a better targeting of resources to improve hazard vulnerability.

Given substantial variability in local physical, political, and social conditions, the existing voluntary framework for local hazard mitigation may have advantages in allowing locals to identify "low-hanging fruit" while tailoring their hazard mitigation plans to local factors and concerns. What drives community participation in CRS within the current voluntary framework is an important policy question. In chapter 3, we test a number of hypotheses offered by previous researchers regarding factors that motivate local hazard management initiatives through an examination of patterns in CRS participation across all 100 North Carolina counties from 1991 to 2002. Specifically, we examine the influence of flood experience, hydrological risk, local capacity, and socioeconomic factors on county hazard mitigation decisions. Results indicate that flood history and physical risk factors increase likelihood of local hazard mitigation adoption. Federal and state agencies should seek to provide a stronger framework for grants-in-aid, low interest loans, and technical assistance to help build resilient communities before disasters instead of focusing attention on post-disaster rebuilding efforts. Moreover, community assistance programs that emphasize scientific applications in estimation of potential flood losses could increase the adoption of flood hazard mitigation in vulnerable areas. We find evidence that the probability of CRS participation is lower in counties with a greater proportion of senior citizens. While we do not observe senior migration rates in our data, age structure of the community could reflect retiree migration patterns. Migrating seniors can induce significant potential for economic development in scenic, rural communities, and local elected officials may focus more on this development opportunity (which can create significant economic benefits and a larger tax base) and less on potential changes in vulnerability to natural hazards that can be associated with rapid economic development. Migrating retirees from outside the state may be less aware and knowledgeable of flood hazards and thus could put less pressure on local government to engage in flood hazard mitigation. As the U.S. population continues to age, it becomes increasingly important to consider elders in pre-disaster mitigation planning. Our result has implications for targeting of information and outreach programs which could be conveyed through public meetings, media, or other venues where senior members of the communities could be well represented.

The description of flood hazard mitigation activities in the *CRS Coordinator's Manual* focuses primarily on the process used to assign mitigation points, with less attention paid to the potential local benefits of mitigation activities, in terms of property damage avoided and lives saved. These factors could be very difficult to quantify from a general standpoint. The real limitation in such a demonstration is establishing an accurate counterfactual – what would flood impacts have been in the absence of existing hazard mitigation projects. In chapter 4, we use the propensity score matching (PSM) methods to correct sample selection bias due to observable differences between the CRS participants and comparison groups. The methodology in this chapter makes important advances in understanding how to measure and conceptualize the performance of a mitigation program as it applied to reducing the adverse effects of flooding. Our study shows the potential for applying PSM in the evaluation of the causal effects of CRS mitigation projects on damage reduction. The selection of covariates is confirmed to be important. For the DID exercise, we find evidence that time-invariant unobservable effects contribute to selection bias which may lead to a downward bias in the estimation of treatment effects. Although there is substantial variation in the results, the findings show that all of the effects are in the same direction, indicating that CRS effectively reduces average property damage due to the flood hazard. As such, our results give considerable insight into the development of future evaluation strategies aimed at addressing the effectiveness in mitigation s activities. Examples or brief case studies could be useful to illustrate the benefits of flood risk management in the future. FEMA and state agencies could take a more active role in demonstrating successful hazard mitigation programs after local flood events, especially focusing on differences between CRS and non-CRS participants. Cases of successful hazard mitigation could be publicized in the wake of catastrophic events, with the goal of transferring effective mitigation strategies to other hazard-prone NFIP communities. These information conduits could help local governments understand and visualize the potential benefits of the flood hazard mitigation projects, which could strengthen their own flood protection programs.

The previous chapters demonstrated that community characteristics can influence the local government decision-making process and the amount of hazard mitigation that takes place locally. Local governments are able to adjust their mitigation policies and planning regulations to react to periodic natural hazard events such as floods, hurricanes, and earthquakes, and from changing environmental and socio-economic conditions. In chapter 5, we describe the course of CRS creditable activities chosen by the local authorities as a policy learning process. This policy learning reflects political dominance that influences initial adoption of new mitigation projects and regulations in the local mitigation policy design, but also substantive policy processing and feedback of flood risk management experience. The goal of this study is to provide an empirical verification of whether the dynamic mechanism exists in the (self) policy learning process within the CRS communities. The empirical evidence provides advice about policy design and further information for those who seek a better understanding of the relationships between policy formation and outcomes.

The analysis is performed using data pertaining to 100 NC counties for the period 1995-2010 in a dynamic panel framework. The dynamic panel data model includes lag of dependent variable (aggregated CRS score) to accommodate the "theory of state" in an intuitive manner. We apply the GMM approach and instrumental variables to deal with endogeneity issues. While our results demonstrate that the current policy is significantly influenced by some environmental and social stimuli, such as vulnerability, tax revenues, population levels, etc, the analysis suggests that policy learning is in fact a more complex phenomenon that also responds to previous policy development. Holding flood experience, hydrological risk factors, and level of financial resources constant, once the local governments regulate their floodplains beyond the minimum required by the NFIP, it tends to carry on incrementally over time, despite changes in staff and shifts in changes and the local political regimes. This suggests a commitment amongst some local governments to high levels of floodplain management activities that can benefit the entire community. Furthermore, we note that marginal increases in CRS points are relatively more difficult to achieve when initial points have already been obtained, since it generally requires increased resource allocation and continued political support. The findings would support the establishment of low-interest loan programs or state grant-in-aid programs targeting counties without adequate resources, high risk factors, and high potential for floodplain development. Subsidized interest rates and outright grants could be economically justified in terms of foregone disaster aid and lower business interruption (resulting in lower tax revenue losses).

Study of local government behavior in adapting to natural hazards warrants serious investigation. In particular, we examine an innovative incentive policy under the Community Rating System (CRS) of the National Flood Insurance Program. CRS is unique and potentially an important federal experiment since it incentivizes community behavior to mitigate, rather than mandates or withhold funds (which is the more common approach of state and federal regulation). We argue that given growing risks, uncertainties and complexities required to effectively adapt to environmental change, communities will increasingly serve a critical role in building societal resiliency to future vulnerabilities posed by natural hazards. The dissertation is a contribution to the limited quantitative literature exploring the influence of flood experience, hydrological risk, financial capacity, and socio-economic factors on local hazard mitigation decisions at the county level. We focus on CRS participation decisions and point totals at only on the county level, primarily because data on covariates are not readily available at lower jurisdiction levels.

There are promising extensions to this research. CRS community divisions rest on a multi-jurisdictional scale which includes towns, cities, and counties. Therefore, the county and nested municipalities may exhibit divergent flood-loss reduction efforts with separate floodplain management ordinance and regulations. A multilevel model provides a framework to analyze how the covariates measured at different level affect the outcome variable. Municipalities in the same county tend to be more alike in their social and environmental characteristics than the ones from other counties. For example, under the multi-jurisdictional mitigation planning context, hazard identification, management, and specialized equipment and expertise are generally similar between nested municipalities. To ignore this relationship risks overlooking the importance of county effects and may render invalid results from traditional statistical analysis. A multilevel analysis could account for the variance in the outcome that is measured at the lowest level by considering information from all hierarchical levels. We recommend a study that incorporates the hierarchical structure, which may provide more satisfactory answers to the question of how to forge a better understanding of community decision making at the municipality scale, as related to natural hazards. It is also of considerable interest in the relative ranking of counties, using the performance of its nested municipalities in terms of mitigation level after adjusting for the cluster characteristics. Since we need to combine county level data with municipality level data in the multilevel modeling, data source may continue to provide significant constraints on analytical capabilities. A more detailed and thorough analysis of the relationship between hazard mitigation at the level of counties and cities & towns remain an important area for future research.

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Appendix 1: Population Weighted Measurement of County CRS Points.

CRS community divisions rest on a multi-jurisdictional scale which includes towns, cities, and counties. Therefore, the county and nested municipalities may exhibit divergent flood-loss reduction efforts with separate floodplain management ordinance and regulations. In their study, Brody, et al. (2009) use population-adjusted measures of CRS activities, CRS score, and community-level covariates to account for nested municipalities and the county itself in their county-scale analysis. Based on Brody's work, the figure and table below show the logic of our measurement for population weighted CRS points. In the figure, Pitt County and incorporated municipalities of Ayden, Bethel, Falkland, Farmville, Fountain, Greenville, Grifton, Grimesland, Simpson, and Winterville have learned different CRS points. First, we divided the population of each community by the total county population to derive the population ratio. Second, we obtain the population weighted CRS points for each community by multiplying the CRS points of each community with its population ratio. Finally, we add up all weighted CRS points to derive the population weighted point for Pitt County. By this measurement, our dependent variable could summarize the CRS mitigation activities in all nested municipalities and the county itself.

Figure: Measurement of Population Weighted CRS Points for County (An Example for Pitt County, NC 2005)

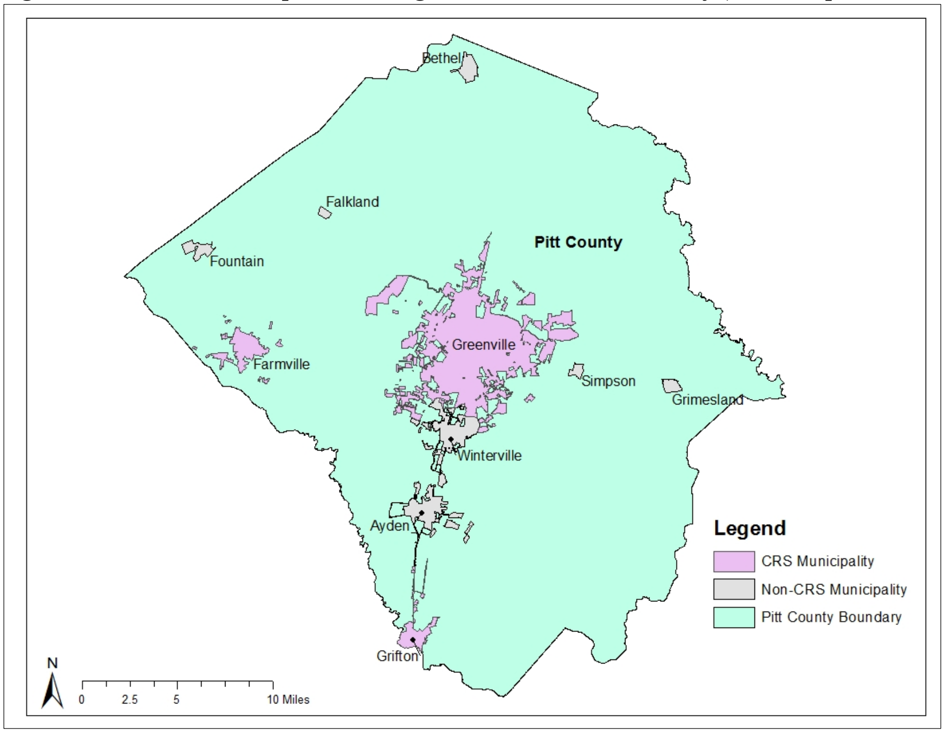

Table: Measurement of Population Weighted CRS Points for County (An Example for Pitt County, NC 2005)

Community	County Population	2005 CRS Points	2005 Population	Population Ratio	Weighted CRS Points
Ayden	133759	0	4782	0.0358	0
Bethel	133759	0	1766	0.0132	0
Falkland	133759	0	114	0.0009	0
Farmville	133759	1110	4611	0.0345	38.264
Fountain	133759	0	550	0.0041	0
Greenville	133759	1412	68852	0.5147	726.822
Grifton	133759	2926	2378	0.0178	52.019
Grimesland	133759	0	441	0.0033	0
Simpson	133759	0	471	0.0035	0
Winterville	133759	0	7682	0.0574	0
County unincorporated area	133759	1035	42112	0.3148	325.854
Pitt County Population Weighted CRS Points					**1142.960**

Appendix 2: Generalized Least Square (GLS) and Feasible Generalized Least Square (FGLS).

Heteroskedasticity means the standard deviations of a variable are non-constant, which causes OLS no longer asymptotically efficient in the estimation. The response to the detecting of heteroskedasticity is to use the GLS method. GLS assume:

$$Var(u_i|x_i) = E({u_i}^2|x_i) = \sigma^2 h(x_i)$$

where $h(x)$ is some function form of the explanatory variables. Because:

$$E\left(\left(\frac{u_i}{\sqrt{h_i}}\right)^2\right) = \frac{E({u_i}^2)}{h_i} = \frac{\sigma^2 h_i}{h_i} = \sigma^2$$

Therefore, we transform the original equation:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_n x_{in} + u_i$$

to:

$$y_i/\sqrt{h_i} = \beta_0/\sqrt{h_i} + \beta_1(x_{i1}/\sqrt{h_i}) + \beta_2(x_{i2}/\sqrt{h_i}) + \cdots + \beta_n(x_{in}/\sqrt{h_i}) + u_i/\sqrt{h_i} \qquad (1)$$

Or

$$y_i/\sqrt{h_i} = \gamma_0 + \gamma_1 z_{i1} + \gamma_2 z_{i2} + \cdots + \gamma_n z_{in} + \varepsilon_i$$

where $z_{in} = x_{in}/\sqrt{h_i}$ and $E({\varepsilon_i}^2) = \sigma^2$. γ_n is called GLS estimator.

Because we don't know the function form of $h(x_i)$ in most case, FGLS estimator uses $\widehat{h_i}$ instead of h_i in the equation (1). The step of FGLS is described in Woodridge (2002):

1) Run the regression of y_i on $x_1, x_2, \dots, x_n$ to obtain the residual, $\hat{u}_i$.
2) Run the regression of log $(\hat{u}_i^2)$ on $x_1, x_2, \dots, x_n$ to obtain the fitted value, $\hat{g}_i$.
3) Estimated h_i: $\widehat{h_i} = \exp$ $(\hat{g}_i)$.
4) Run the regression of equation (1).